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IMPROVING THE TAIWAN MILITARY'S DISASTER RELIEF RESPONSE TO TYPHOONS

by

Hung-xin Li

June 2015

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IMPROVING THE TAIWAN MILITARY'S DISASTER RELIEF RESPONSE TO TYPHOONS

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ABSTRACT

Taiwan is prone to many natural disasters, especially typhoons. This thesis adapts an existing stochastic prepositioning optimization model to create a tool for Taiwan military disaster recovery planners, and then uses experimental design techniques to systematically explore solutions. The goals are to minimize the expected number of casualties and unmet commodities demands, and to determine the average number of workers deployed in response to each scenario. A design of experiments methodology is applied to the optimization model to reveal how uncertainty in the parameters translates to uncertainty in objective function values. The approach can also identify the parameters with the greatest impact on the objective function, and result in more robust solutions. The analysis demonstrates that it is not always necessary to spend as much money and deploy as many workers as in the past in order to get the best results. Additionally, the approach shows how a decision maker, with more accurate and current weather reports, can refer to the path and intensity of typhoons while making rescue plans. In summary, this research shows that there is great potential for quantitative methods to improve the disaster-relief planning process.

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TABLE OF CONTENTS

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LIST OF FIGURES

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LIST OF TABLES

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LIST OF ACRONYMS AND ABBREVIATIONS

AA, AAn	Affected Area, nth Affected Area
AP	Affected Population
AB	Army Base
AFB	Air Force Base
C130, C17	Air Force Aircraft (used in carrying cargo)
CSV	Comma Separated Value
DOE	Design of Experiment
DP	Displaced Population
EP	Emergency Population
EPA	Environmental Protection Administration
EOC	Emergency Operations Center
GAMS	General Algebraic Modeling System
GUI	Graphical User Interface
HMMWV	High Multipurpose Mobility Wheeled Vehicle
JMP	Statistical Software
MFH	Mobile Field Hospital
MND	Ministry of National Defense
MOE	Measure of Effectiveness
MoT	Means of Transportation
MOTC	Ministry of Transportation and Communication
NCDR	National Science and Technology Center for Disaster Reduction
NDC	National Development Council
NOB	Nearly Orthogonal-and-Balanced Design
NOLH	Nearly Orthogonal Latin Hypercube
OA	Operation Area
ODM	Office of Disaster Management
POM	Prepositioning Optimization Model
RL, RLn	Relief Location, nth Relief Location
ROC	Republic of China
SSE	Sum of Squares Error

TO	Theater of Operation
TWB	Taiwan Weather Bureau

EXECUTIVE SUMMARY

Taiwan is vulnerable to many natural disasters, with typhoons being one of the most destructive natural hazards, causing damage to infrastructures and economic losses. The Ministry of National Defense (MND) is committed to disaster assistance. However, planning and conducting a disaster-relief mission is challenging due to the uncertainty inherent in natural disasters and the demand created by them. The MND does not currently have any analytical tool that will assist in disaster management preparation and rescue planning. Although studies have been conducted on post-disaster data, no quantitative models have been established to evaluate the disaster management process. It is therefore imperative to develop a quantitative method that assesses the disaster relief processes. The results from the analysis could be used to evaluate risk and aid in determining the effectiveness and resource feasibility of alternatives while maintaining the desired outcomes.

This thesis adapts an existing stochastic Prepositioning Optimization Model (POM) to create a tool for the Taiwan MND disaster recovery planners, and uses experimental design techniques to systematically explore solutions to the model. It is important to note that natural disasters are inherently uncertain, and so are the needs for assistance they create. Quantitative approaches to assist in disaster relief processes must recognize this uncertainty. We analyze the past 60 years of Taiwan typhoon data, and the relationship between region and typhoon characteristics. Based on historical data, the baseline scenario for this thesis is established. We model a network of five Affected Areas (AAs) and eight Relief Locations (RLs), five typhoon scenarios of different intensity, and several budget levels for expansion of the initially prepositioned resources. The goal is to minimize the expected number of casualties and unmet commodities demands, and to determine the number of workers deployed in responding to each scenario.

The design of experiments (DOE) approach surrounding the optimization model allows the data and assumptions that are made in the model to include more variability. In this experiment, several types of model parameters are varied: (i) the numbers of

available relief workers; (ii) budget, penalty for inability to transport commodities, and survival rate of the emergency population; and (iii) the probability of occurrence of each scenario. More importantly, this approach allows the analyst to determine the extent to which different sources of uncertainty affect the nature and the quality of the solution, and hence to find robust solutions given the unpredictable nature of natural disasters. This is advantageous because required data are not always readily available.

With the data and assumptions in this thesis, the POM solutions only partially address the question of how to improve disaster relief operations. Above a certain level of budget and number of available relief workers, the results may indicate large amounts of spending without a corresponding improvement in the primary objectives of saving lives and transporting displaced people. While further enhancements to POM would make it easier to determine cost-effective resource allocation decisions, the results in this thesis clearly demonstrate that it is not always necessary to spend as much money and deploy as many workers as in the past in order to get the best results. Additional insights gained from our analysis include how a decision maker can, with more accurate and current weather reports, exploit the path and intensity of typhoons to make rescue plans. Continued cooperation between Taiwan MND and Taiwan Weather Bureau (TWB) is recommended.

In summary, the motivation for this thesis is a desire to assist Taiwan MND planners and help the military respond to disaster assistance requests in a timely and effective manner. This research shows that there is great potential for quantitative methods to assist in this process.

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I must first thank my thesis advisor, Professor Susan Sanchez, for her help in forming and writing this thesis. After countless hours of meetings, she provided me with the knowledge to understand the design of experiments (DOE) and how to manipulate it with the prepositioning optimization model (POM). I would like to thank Professor Samuel Buttrey for giving me advice on data analysis and Professor Javier Salmeron for explaining the POM, which was the basis of this thesis.

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I. INTRODUCTION

A. BACKGROUND

Asia and the Pacific Islands suffer more natural disasters than any other area of the world (United Nations Environment Programme [UNEP], 2001). In 2005, the report entitled Natural Disaster Hotspots—A Global Risk Analysis, issued by the World Bank, indicated that "Taiwan might be the place most vulnerable to natural hazards on Earth, with 73% of land and population exposed to three or more hazards per year" (Lin, 2008). Taiwan is situated upon a tectonic fault line that places the island at high risk of earthquakes and volcanic activities. The island also has experienced a growing number of typhoons that are increasing in strength due to rising ocean temperatures in the Pacific. Lastly, Taiwan features a landscape contoured by some of the highest mountains in the Asia-Pacific region, creating a sharp drop to the ocean that produces rapid runoff of rainwater and floods in the alluvial plains on the western side of the island.

Tropical cyclones are called "typhoons" in the Western Pacific and "hurricanes" in the Atlantic and the East Pacific Oceans. Typhoons are always accompanied by heavy rains, strong winds, and large waves. They are responsible for at least 70% of Taiwan's natural disasters. Figure 1 from the Republic of China (ROC) Environmental Protection Administration (EPA) shows the tracks of all tropical cyclones in the Northwest Pacific area between 1980 and 2005, and Taiwan is located in an area of high intensity. On average, Taiwan is hit by 3.6 typhoons a year, resulting in USD $600 million in economic losses (National Science and Technology Program for Hazards Mitigation [NAPHM], 2011). Meanwhile, the incidence of typhoons in Taiwan has risen from an average of 3.3 per year in the 20th century to an average of 5.7 per year after 2000. After 2000, experts also note a rising number of medium-strength typhoons and fewer minor typhoons (Stokes & Ma, 2011). The increasing number of typhoons threatens the island.

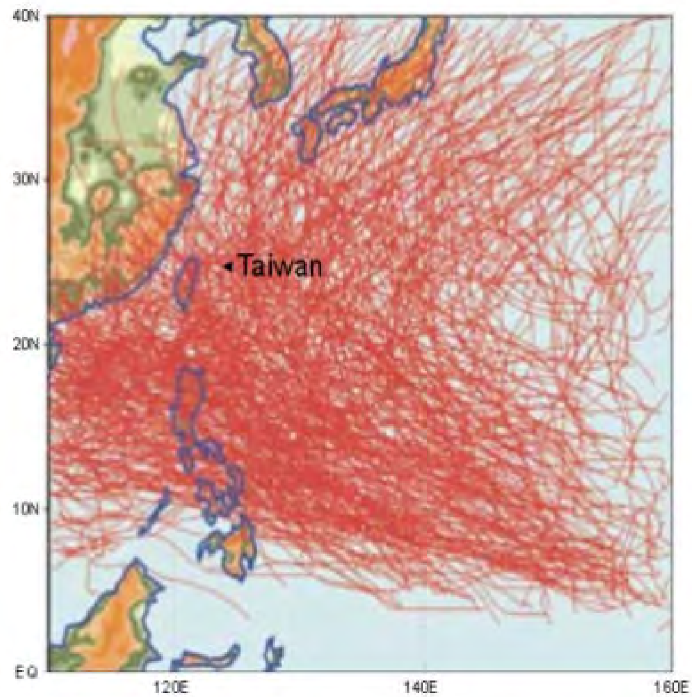


Figure 1. The track of typhoons in the Northwest Pacific (from Stokes & Ma, 2011).

One of the massive typhoons to hit Taiwan was Typhoon Morakot in August 2010. It produced copious amounts of rainfall, totaling 2,777 mm (109.3 inches). This extreme amount of rain triggered enormous mudslides and severe flooding throughout southern Taiwan. One mudslide buried the entire Xiaolin Village. A total of 461 people perished and 192 others are still listed as missing. The total damage to property was more than USD $3.3 billion (NAPHM, 2011). After Typhoon Morakot, the ROC President Ma Ying-jeou increased the number of soldiers working in rescue and recovery actions to 46,000. Such personal tragedy and huge amount of property lost in Xiaolin Village motivated the ROC government to enhance the effectiveness and performance of the existing disaster emergency management system. In 2011, the Executive Yuan (one of five branches of the ROC government) passed amendments to the Disaster Prevention and Response Act (DPRA) that enable Taiwan authorities to continue to work with the ROC Armed Forces to actively prepare for disaster prevention and relief in the event of complex disaster.

B. CURRENT MILITARY EMERGENCY PLANNING

Before the DPRA was implemented by the Emergency Operations Center (EOC), the ROC government tasked each city to devise an individual emergency plan to respond to disasters, and to call the local fire department for further assistance in rescue and repair operations if needed. After the Typhoon Morakot crisis, the ROC government realized that multiple counties would be affected during a large disaster, and a high-performance and more professionalized central emergency management system would be needed. Therefore, the EOC focused on rebuilding the organizational framework at the central government level and in coordination with the ROC Armed Forces (Office of Disaster Management [ODM], 2010).

The ROC Armed Forces carry out disaster relief missions in accordance with the Executive Yuan's DPRA and the "Regulations on the ROC Armed Forces' Assistance in Disaster Relief" to protect the safety of citizens' lives and assets. Furthermore, with "disaster relief" listed as one of its main missions, the ROC Armed Forces is building disaster relief capabilities under the assumptions that disaster relief is akin to fighting a battle and that they should emphasize disaster prevention over disaster relief, and prioritize disaster avoidance over disaster prevention. In preparation for a major disaster, the ROC Armed Forces "implements active measures to prepare for disasters in advance, pre-deploy troops for disaster relief, and ensure readiness for rescue operations under the premise of not affecting combat readiness, and fully engages in disaster relief" (Ministry of National Defense [MND], 2011, p. 11).

During the disaster prevention and preparedness stage, military bases in each theater of operation (TO) will pre-deploy troops in areas prone to mudslides and flooding 24 hours before a typhoon lands, when there is more flexibility for maneuvers. The commander will contact heads of local governments and notify them of the number of troops deployed, their location, and capabilities for further decision making. For medical support, Armed Forces General Hospitals are capable of organizing a total of 158 medical and health service support teams. These teams are manned by 537 medical professionals and paramedics and equipped with 158 ambulances (MND, 2011). Military hospitals, medical teams, public hospitals, and civilian hospitals in local areas will jointly establish

a liaison and report system aimed at integrating resources from hospitals and field medical units as well as enhancing capacity and mission effectiveness of emergency medical support.

The ROC Armed Forces plan to use several military bases in all theaters of operations (including the islands of the Kinmen, Matsu, and Penghu) for the temporary accommodation of disaster victims. This provides a total capacity to house 16,551 people during major disasters. Furthermore, gymnasiums, military conference halls, and school classrooms can be immediately converted into high-density shelters (no beds) in the event of a complex disaster, with a capacity of 36,961. The total capacity of low- and high-density shelters is 53,512 (MND, 2011). The shelters may be adjusted at any time to complete the mission of accommodating disaster victims. The ROC Armed Forces also provide military vehicles and aircraft to transport the victims and the commodities during disaster relief efforts. We use those numbers as upper bounds in our budget.

Each year, the ROC government organizes regional and local disaster relief exercises to test emergency response mechanisms and operating procedures. Figure 2 displays the process for requesting the supplies from the MND after a typhoon warning has been issued. The EOC and city provide quick but limited responses, such as providing a small amount of water and food. The MND plays an important role: Once it receives a request from the EOC or an affected city, it provides the majority of relief workers, transport vehicles, and supplies.

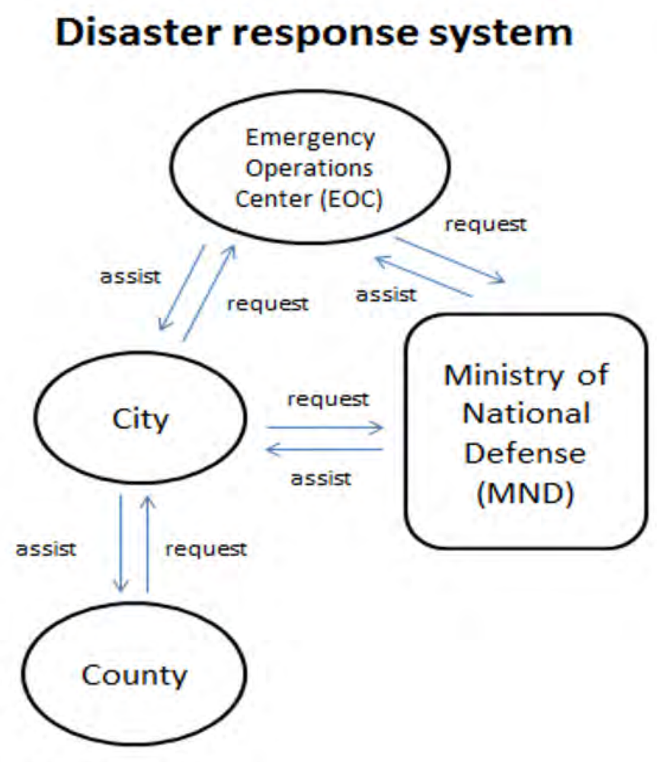


Figure 2. Disaster response system diagram.

The ROC Armed Forces will continue to assist local governments at each level in carrying out disaster relief work, when requested, so as to minimize the damage they sustain. This response system has been the process for the past 10 years, and through hundreds of typhoons, with little improvement to the procedure.

C. THESIS MOTIVATION

Even though the potential for a strong typhoon crisis exercise in Taiwan has been discussed extensively by both the EOC and the MND, a detailed analysis of the prepositioning of deployed personnel before the disaster (and its effect on the disaster's aftermath) has not been performed. That phase of the plan is important because the efficiency of subsequent logistics, such as the distribution of supplies to affected areas during the disaster, is highly dependent on those strategic personnel estimates. Part of this analysis must be the accurate estimation of personnel requirements.

Inaccurate personnel estimates for typhoon response, as for any major operation, can cause major disruption of training, patrols, and day-to-day operations, and can produce a sudden strain on base support services (barracks, food service, utilities, etc.). This is particularly evident when requirements have been overestimated, as has happened in the vast majority of occasions. For example, in the author's own experience, massive numbers of people have been called up without clear direction as to how they should be used, or where they should go. Underestimating can be even more detrimental in other ways, as it can impede the distribution of relief supplies. Developing a tool that supports the ROC Armed Forces' personnel prepositioning requirements with historical data–based estimates would help ensure the conservation of limited resources while also ensuring an effective response to disasters.

D. LITERATURE REVIEW

Nissen (2011) applies contingency theory to model the 2004 Indian Ocean disaster, in which an earthquake and tsunami killed over 230,000 people in 14 countries. He realizes that many of the operations are dynamic, and that using a static statistical model does not fully capture the real situation. He simulates six months of relief efforts by governmental and nongovernmental organizations in several time steps, and compares his simulated results to actual relief effort data. One of the results he observes is that dynamic models are more reliable when modeling large international responses to disasters.

Heidtke (2007) focuses on the problem of prepositioning and delivering critical commodities following a disaster. He discusses several strategies that help ensure that commodities are available at the right time and location: prepositioning, preemptive federal action, time-phased deployment, and surge transportation. His approach employs an earlier version of the optimization model used in this thesis, and applies it to a hurricane scenario and to a nuclear explosion scenario in the Washington, DC, metropolitan area. He shows that stochastic optimization can be a useful strategic tool to help decision makers plan for a given type of disaster under uncertainty in its severity.

Salmeron & Apte (2010) further study the use of stochastic optimization for strategic prepositioning of resources in a natural disaster, and provide references for earlier work in deterministic disaster relief modeling. They use a two-stage prepositioning optimization model (POM) to determine the decisions that have to be made prior to and after a disaster. They include factors such as vehicles used to rescue people or deliver supplies, casualties, population needing mass housing, and expansion possibilities, as limited by the available budget. The study determines the optimal prepositioning of resources given probabilities for multiple possible disaster scenarios.

Farlow (2011) applies POM to represent and analyze the flooding disaster problem in the Sacramento region. He discusses that POM recommends where to preposition and/or expand warehouses, healthcare personnel, ramp space, and transportation vehicle capacity in order to evacuate the victims after a flood disaster occurs. He also analyzes several budget levels for expansion of the initially prepositioned resources. The study demonstrates the application of POM optimal prepositioning of resources given probabilities for multiple possible disaster scenarios.

Gardner (2015) uses POM as a basis for an asset allocation model for naval logistics planners, and then uses design of experiments (DOE) techniques to systematically explore solutions to the model. She demonstrates that a DOE methodology on an optimization model can reveal how uncertainty in the parameters translates to uncertainty in objective function values, identify the parameters with the greatest impact, and find robust solutions.

Lee, Ghosh, & Ettl (2009) describe a tool for distributing emergency supplies after disasters strike. They use a combination of optimization tools for modeling the supply chain and distribution method, and link these with simulation modules for generating disaster severity and demands. They make several changes to their base case model, such as increasing the amount of pre-positioned supplies or using different shipping rules, to identify a few potential improvement opportunities for disaster response planning. Lee, Ghosh, & Ettl (2009) also provide a number of references for operations research models and applications to emergency response, but state that most of

the published research focuses on a particular type of disaster and does not cover the full spectrum of supply chain modeling to disaster severity modeling.

With the exception of Gardner (2015), those who evaluate different alternatives from their base case models tend to focus on one-at-a-time changes from the base case, or a small number of combinations of two or three model inputs or parameters. A difficulty of this approach is that it limits the opportunities for insight. A large-scale DOE approach is needed so that excursions from the base case are generated in a structured manner (Kleijnen, Sanchez, Lucas, & Cioppa, 2005; Sanchez et al., 2012).

E. THESIS OBJECTIVES AND THESIS ORGANIZATION

The objective of this thesis is to show how applying large-scale simulation experiments to optimization models can help improve the ROC's plans for responding to natural disasters. Specifically, this combined approach can reveal plans that reduce the expected number of casualties and unmet commodities demands, and determine the proper expected number of workers deployed in response to each scenario.

The remainder of this document explores the use of a variant of POM, with additional relief worker constraints, in selected scenarios associated with five main regions in Taiwan. Chapter II introduces different approaches to plan and model typhoon disasters. First, it summarizes the past 60 years of Taiwan typhoon data and the relationship between regions and typhoon characteristics. Based on historical data, the baseline scenario for this thesis is established. This thesis introduces the POM with extra constraints of available relief workers added, and discusses how it can be used to guide in the future of Taiwan Military Force deployed plans. The selection process for the affected areas (AAs), relief locations (RLs), and military vehicles used is described at length, and is based on each military defense zone. The different populations involved in a typhoon disaster are designated. The data gathered for this thesis and their input into the model are explained. This includes the scenario selection and other assumptions made to complete the input data. Chapter III explains the results of the POM, based on running 512 variants of the model. These variants involve changing settings for some of the model assumptions, such as the maximum numbers of workers available at different locations,

the maximum budget available for relief efforts, and the probabilities associated with different typhoon trajectories. They are constructed using design points from a nearly orthogonal-and-balanced (NOB) design, developed for exploring large-scale simulation experiments (Vieira, Sanchez, Kienitz, & Belderrain, 2013). Chapter IV summarizes our findings and describes future work to help planning for other disasters. The appendix contains a detailed description of the mathematical formulation of POM.

F. HISTORICAL TAIWAN TYPHOON DATA

Due to the high frequency of typhoons crossing Taiwan, the Taiwan Weather Bureau (TWB) has established processing software to record each typhoon's data for further analysis. At the same time, this system can forecast a typhoon's path and the potential track area for up to 72 hours. Figure 3 is a screenshot of this TWB typhoon forecast system when a typhoon occurs. Using this software, we can collect the following data: intensity of the typhoon, typhoon center pressure, possible crossing path and time, amount of rain, and radius of the storm.

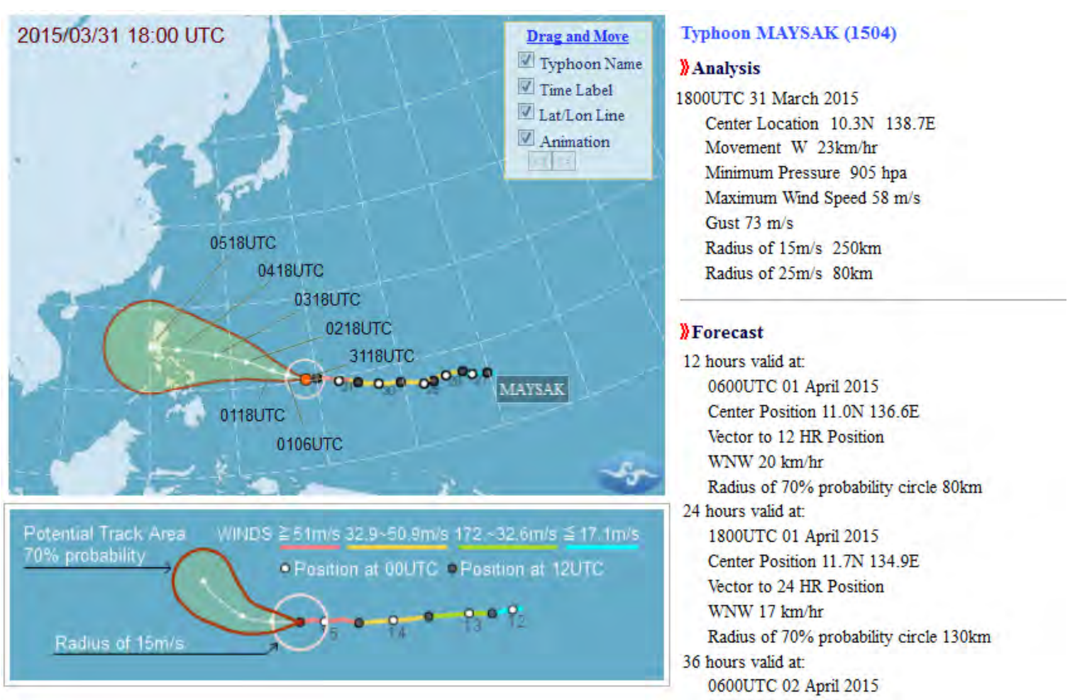


Figure 3. Typhoon forecast and information (from TWB website, http://www.cwb.gov.tw/eng/, 2015).

This thesis uses the typhoon data from 1958 to 2014. There have been a total of 395 typhoons recorded. In the following analysis, we first use JMP© software (SAS, 2015), an interactive statistical software package, to create graphs and histograms to reveal the relationship between the recorded elements such as crossing path, typhoon intensity, and terrain. We then use these data to develop the baseline scenario to be used in the following simulation runs.

The intensity of a typhoon is measured by the maximum average wind speed near the center, and falls under the three categories shown in Table 1. The Beaufort scale is an internationally recognized system for classifying a typhoon based on the maximum wind speed at the center. A storm is recorded as a low-intensity typhoon if its maximum wind speed at the center reaches 34 to 63 knots (17.2 m/s–32.6 m/s), or 7 on the Beaufort scale. Medium typhoons in the data represent maximum wind speeds at the center reaching 64 to 99 knots (32.7 m/s–50.9 m/s), or 12–15 on the Beaufort scale. A typhoon that has maximum wind speeds at the center at or exceeding 100 knots (51.0 m/s), or 16 on the Beaufort scale, is labeled as a strong typhoon in our data set.

Table 1. Categorization of the intensity of typhoons.

Typhoon intensity	**Maximum wind speed near the typhoon's center**			
	km/hour	**m/sec**	**Knot (mile/hour)**	**Beaufort scale**
Tropical storm (low intensity)	62–17	17.2–32.6	34–63	8–11
Typhoon (medium intensity)	118–183	32.7–50.9	64–99	12–15
Typhoon (strong intensity)	at or above 184	at or above 51.0	at or above 100	at or above 16

According to the data from Table 1, of the past 395 typhoons, 43% were of medium intensity, 29% were of strong intensity, and around 27% were of low intensity. The distribution histogram from JMP is shown in Figure 4.

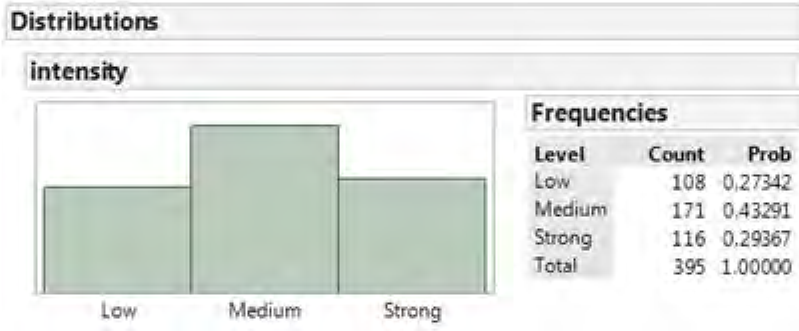


Figure 4. Intensity distribution of the study data set.

A typhoon in the Pacific can happen anytime throughout the year, yet most typhoons happen between July and September. Figure 5 shows that typhoons come to Taiwan in late April at the earliest, and November at the latest. July, August, and September see most of the typhoon strikes.

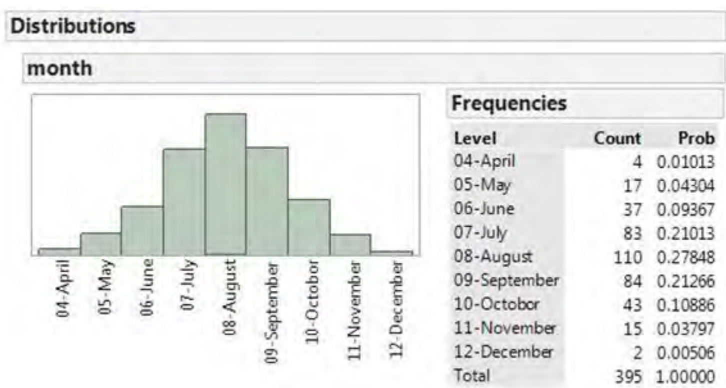


Figure 5. Monthly distribution of the study data set.

The direction of a typhoon's movement is generally subject to the control of large-scale airflow. The typhoons occurring in the Northwestern Pacific Ocean, mainly steered by the Pacific subtropical high-pressure circulation, are mostly westbound. When they reach the vicinity of Taiwan or the Philippines, which are always at the edge of the Pacific subtropical high-pressure region, they vary in their paths, with some going on westbound, some turning northeast, and some even lingering or moving in a circle. In general, a typhoon follows a regular path when the large-scale steering flow is clearly

identifiable, and behaves more unpredictably otherwise. The general typhoon crossing paths are shown in Figure 6.

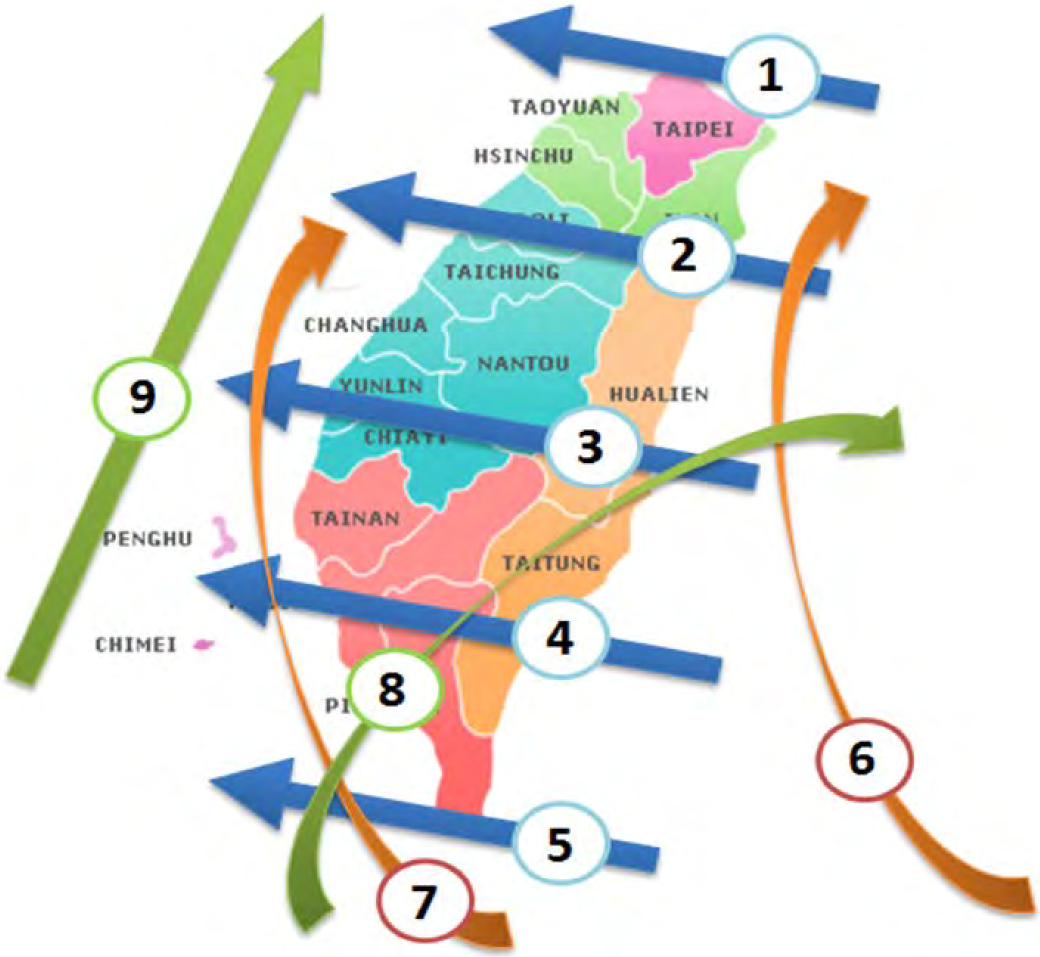


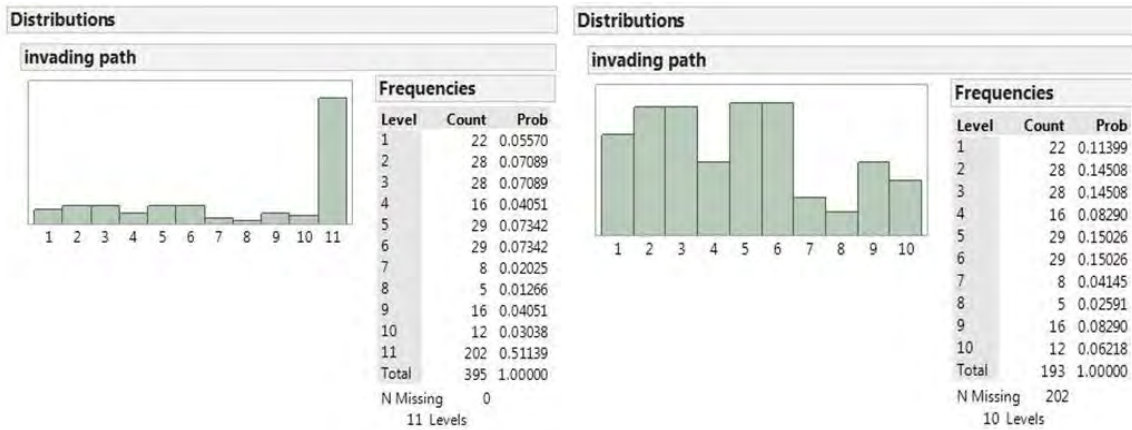
Figure 6. Schematic diagram of typhoon tracks crossing Taiwan.

Table 2 produces further details about how the impacting paths are categorized. Categories 1 through 9 are those tracks shown in Figure 6. Category 10 typhoons are those that crossed Taiwan but did not fit into categories 1 to 9. Category 11 typhoons are those that did not cross Taiwan.

Table 2. Categorization of the path of typhoons.

Category	Description of crossing path
1	Moving westward or northwestward after passing through Taiwan's northern sea region
2	Moving westward or northwestward after passing through northern Taiwan
3	Moving westward or northwestward after passing through mid-Taiwan
4	Moving westward or northwestward after passing through southern Taiwan
5	Moving westward or northwestward after passing through Taiwan's southern sea region
6	Moving northward along Taiwan's east coast or eastern sea region
7	Moving northward along Taiwan's west coast or the Taiwan Strait
8	Moving eastward or northeastward after passing through Taiwan's southern sea region
9	Moving eastward or northeastward after passing through southern Taiwan
10	Unique paths that do not fit into the above categories
11	Did not cross Taiwan

When a typhoon crosses an area, the wind intensity depends on the typhoon strength, but also the local terrain, the latitude of the area, and the typhoon path. This is true whether or not the typhoon's center passes directly over Taiwan. The complexity of the Taiwan terrain and the diversity of the typhoon paths have resulted in significant variations in wind intensity from area to area. The distribution of crossing paths from the data set appears in the left subplot of Figure 7. Notice that there are 202 path-11 typhoons, those that did not cross Taiwan. For better observation, the distribution plot is also created after filtering out path-11 data. Both distribution plots are shown in Figure 7.



Level	Count	Prob
1	22	0.05570
2	28	0.07089
3	28	0.07089
4	16	0.04051
5	29	0.07342
6	29	0.07342
7	8	0.02025
8	5	0.01266
9	16	0.04051
10	12	0.03038
11	202	0.51139
Total	395	1.00000

Level	Count	Prob
1	22	0.11399
2	28	0.14508
3	28	0.14508
4	16	0.08290
5	29	0.15026
6	29	0.15026
7	8	0.04145
8	5	0.02591
9	16	0.08290
10	12	0.06218
Total	193	1.00000

Figure 7. Typhoon crossing path distribution plot with and without path-11 data.

The interaction plot between month and crossing path is shown in Figure 8, best viewed in color. The data set including path 11 indicates highest typhoon frequency in August. After filtering out path-11 typhoons, the higher frequency of typhoons following paths 1, 2, and 3 shown in red becomes more evident.

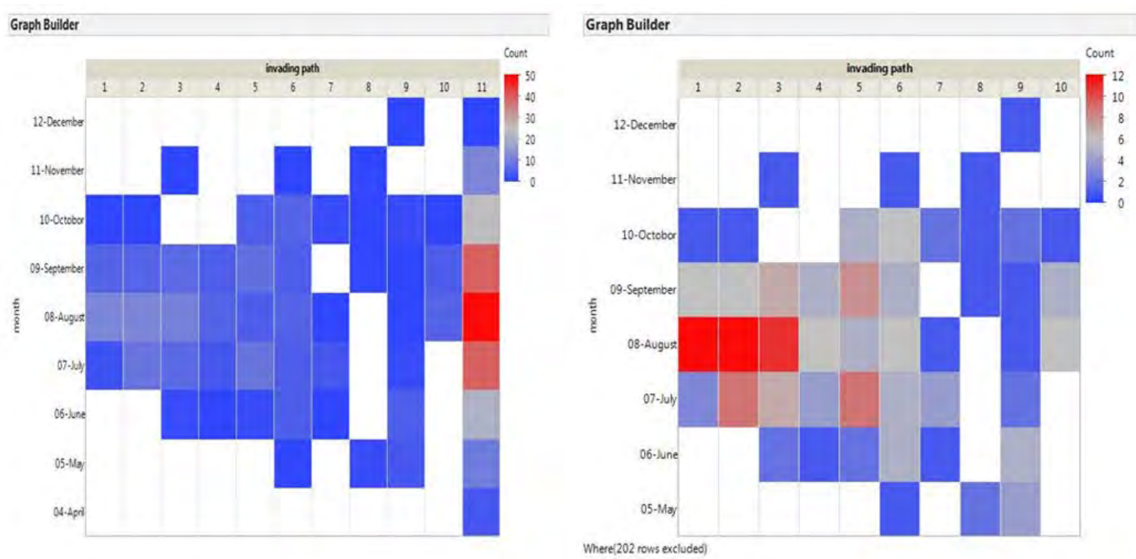


Figure 8. Interaction plots of typhoon crossing path distribution versus month, including and excluding path-11 data.

Based on the historical data and the plots from JMP, the differences can be generally summarized as follows by looking at individual regions. The observations are included in the baseline model scenario:

- Eastern Taiwan: Since typhoons often directly approach this area, it experiences stronger winds than other parts of Taiwan. The wind intensity is the strongest for typhoons in the path categories 2, 3, and 4. Categories 5 and 8 have the second strongest intensities.
- Northern and northeastern Taiwan: This area experiences the strongest wind intensity with typhoons in the path categories 2 and 3, followed by typhoons in path categories 1, 4, and 6.
- Mid-Taiwan: Due to the nearby Central Mountain Range, typhoons cause relatively lower winds except in the path categories 3, 7, and 9, which have winds of strong intensity.
- Southern Taiwan: Due to the nearby Central Mountain Range, typhoons cause relatively lower winds except in the path categories 3, 4, 7, and 9, which have winds of strong intensity.
- Outlying islands: Due to the central mountains serving as a windbreak, the outlying islands such as Kinmen and Matsu are less affected by typhoons than other regions. Path categories 7 and 9 have the highest chance of winds of strong intensity and impact.

This analysis will develop a suggested plan for use when the typhoon can reasonably be predicted to be category 1 through 9. If a category 10 is predicted, then a worst case scenario is used, in which we assume the typhoon impacts both the main island and the outlying islands.

G. MODELING TYPHOON DISASTERS

The prediction of extreme meteorological events such as typhoons builds on conceptual models. The performances of these highly non-linear models are limited, mainly because they lack observation data or because the available data are not properly organized and converted into input data parameters. The disaster can happen at many different locations, levels of severity, and with other unpredictable factors. This can make the planning problem intricate. Furthermore, although multiple approaches to disaster planning have been proposed, they are not always employed.

For example, planners may consider a worst-case disaster like Morakot (ODM, 2010). This scenario posits high precipitation intensity during a short time. Planning

against this pessimistic scenario also protects against many other, less severe situations. However, it places a high demand on the rescue system. Planners may deem that the required preparation against such an extreme event is too conservative and economically unacceptable.

The most common approach for disaster planners is planning for an average scenario based on all the foreseen disaster scenarios. For example, if an area had between 20,000 and 50,000 people in need of evacuation, a plan could be devised for evacuating 35,000 people. Also, planning for the most likely scenario is an attractive method for planners; it allows them to focus on a specific situation. Always planning for the worst-case scenario is simple, but not always economically feasible. However, disaster relief established for the average scenario, again, may not be suitable to apply to another scenario. Since disasters are intrinsically unpredictable, a stochastic model that considers many types of potential events simultaneously can improve the planning for future events.

H. PREPOSITIONING OPTIMIZATION MODEL

POM is a mixed-integer, two-stage stochastic model. The first-stage, pre-disaster, involves expansion of resources such as various facilities and capabilities. The second stage, post-disaster, requires some short-term capability expansions, as well as the deployment of assets to scenario-specific affected areas. Therefore, POM is set up as a multi-objective model with two hierarchical optimization objectives. The primary objective is to minimize the expected number of total casualties (z_1); this includes those EP who are not rescued, EP who are rescued but do not survive, and AP casualties due to unmet commodities. Specifically, we set up a penalty ratio in our first objective account for casualties from the critical population, along with a function that relates the amount of unmet commodities for the AP to the number of deaths that will result. POM assumes that both the EP and AP groups are equally important in the sense that failing to meet either demand results in casualties. The second objective minimizes unmet demand for moving the transfer population ($z2$), but with the additional constraint as an aspiration level (α) based on the first objective optimal solution. In our case, we set the aspiration

level (α) equal to 1%, as did Salmeron & Apte (2010). This means that as the General Algebra Modeling System (GAMS) tries to minimize unmet DP, it does not increase the unmet demand for moving the transfer population by more than 1%.

Figure 9 shows a schematic diagram of the entities present in POM, as well as their movement among various locations. Initially, a number of resource locations are selected to store the needs for disaster prevention. Upon learning of a disaster, it is necessary to have the ability to meet requests by local governments. Once on station for assistance efforts, the relief provider location (RL) deploys troops and vehicles that carry personnel and commodities to affected areas (AAs), and then remove injured survivors from those areas and transport them back to RLs for medical attention.

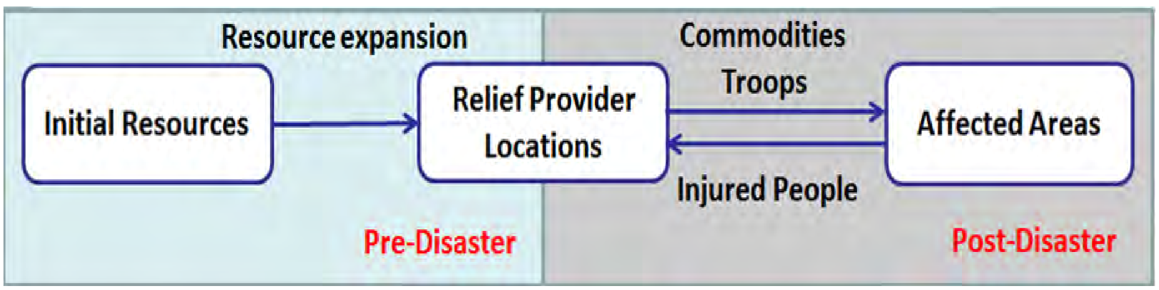


Figure 9. Study model (POM) network.

The populations in these AAs are people that do not successfully evacuate prior to the disaster, and we separate them into three categories depending on their needs. The first category is the emergency population (EP), who are the injured and others in need of emergency evacuation to a facility that can administer medical assistance. The second category is the affected population (AP), who can stay in the AA, but need resources to be delivered in order to survive. The last category is the displaced population (DP), who will need to be transported to an RL for emergency shelter. Note that personnel are not used to transport or otherwise take care of those who died in the initial storm. Each AA has a certain number of each of these three populations in any given scenario. AAs can receive supplies via land or air, depending on their characteristics.

Inputs to the POM that are constant in this study are as follows:

- The EP, AP, and DP populations for a given scenario
- Baseline travel times between each RL to each AA for each vehicle, for a given scenario
- Pounds of needed commodities per person in the AP to avoid a casualty
- Availability of airports to support fixed-wing aircraft and helicopters for each AA
- Data on vehicles available, air capability, medical capability, mass housing capability, and storage capacity for each RL
- Data on DP transport capability, commodity carrying capability, EP transport capabilities, and availability for each vehicle
- Availability for expansion, and associated expansion costs, for warehouses, medical facilities, mass housing facilities, and vehicles.

Resources such as warehouses, medical facilities, and shelter sometimes must be prepositioned at RLs in preparation for (and long before) a disaster. An RL has an assumed initial capacity of each of the above resources, for example, space that can be used for storage of commodities, and mass housing for the DP. If the RL is a medical facility, then it has a limited number of the EP that it can treat. Each RL also has a specific air capability.

Vehicles (air and land) must be available and in place to rescue the EP and transport them to a medically capable RL, transport the DP to an RL with mass housing capability, and transport commodities from an RL to the AP. Each vehicle has its own capability defined in terms of speed, range, availability, cargo carrying capacity, emergency rescue capabilities, and personnel transport capacity. Air vehicles are distinguished from land vehicles in that they may only take off from and land at RLs and AAs that have the capability. Helicopters are included in this model for rescue and relief missions.

Parameters that will be changed in successive runs of this model are

- Budget levels available for use in total maximum expansions ($)
- EP survivor levels (the percentage of EP that survive once transported)
- Maximum number of available troops (relief workers)

Note that the expansion budget and maximum number of troops are decision factors, while the EP survivor level varies from storm to storm, depending on the specific

storm intensity. For this case, we first set the survivor rate to a pessimistic 60%; that is, we assume that 40% of the rescued EP will perish (either before or at the medical facility where they are transported). We also set the survivor rate at 80% and an optimistic 100% to gain more insights.

The POM is multi-objective because the overall goal is minimizing the casualties that result from failing to meet the demands of the EP and AP populations, while maximizing the number of DP moved to RLs. The two-stage, stochastic nature of POM comes from the strategic decisions that need to be made under uncertainty, that is, before the actual scenario is realized. First-stage variables include the expansion of healthcare facilities, warehouses and mass housing shelters at the RLs, and the expansion of ramp space at the AAs. The second stage of the model includes decisions made during the 72 hours after the disaster, including additional vehicles needed, EP rescue and transportation to medical facilities at RLs, transportation and delivery of commodities to AAs, and transportation of DP to RLs. The POM is a mixed-integer program because some of the decision variables must be integer, such as additional vehicles used and numbers of workers used. Other variables are real numbers, such as the quantity of commodities.

Outputs from the POM are as follows:

- Objective function values
- Casualties (persons) by scenario and in expectation over all scenarios (first objective); this is the optimal (lowest) number of casualties
- Feasible expansions of warehouses, medical facilities, vehicles, and mass housing locations
- Supplies used (ft^3 x 1000) by scenario
- Vehicles used by scenario
- Populations (persons) and supplies transported (ft^3 x 1000) by scenario
- Total troops deployed

Note that even if the objective function values from POM are optimal given a particular set of assumptions, they may not be optimal if those assumptions do not hold. Also, although POM will provide a feasible solution for achieving optimal objective function values for any given scenario, this solution may not be optimal in terms of other measures like efficient use of budget. One reason that we are using a DOE wrapper for

the POM model is to explore the robustness of the POM solutions. For completeness, the formulation of the POM (Salmeron & Apte, 2010), with relief workers constraints added, is in the appendix.

I. SITUATION DESCRIPTION AND TAIWAN REGION DATA

1. Data for Affected Areas

We select five AAs, as shown in Figure 10, to encompass the higher population cities that would be affected by a typhoon in the Taiwan region. Each of these areas has an airport or large staging area where commodities can be offloaded. Table 1 describes the AAs and lists their possible offloading locations. AA1 is an isolated island, and AA2 is the east side of Taiwan. AA3 through AA5 make up the west side of Taiwan where most cities are located.

Figure 10. Geographical locations of the five AAs selected for the baseline.

The selected locations in each AA have space available to offload goods. Each AA has its own airport. Each airport has a specific amount of ramp space that can be used for incoming aircraft offload. This is important to quantify so that aircraft do not bring in more commodities than an airport can offload. Because in this thesis it is postulated that all shipping containers carried by vehicles are over five feet tall, we conservatively assume that the ramp space is covered by 5-foot-tall containers. In this manner, the raw square footage of the ramp space can be converted into cubic feet capacity to match that of vehicles and warehouses. Descriptions of the selected AAs are shown in Table 3.

Table 3. Locations and area for offloading in each AA.

Affected area	Description	AA offload location
AA1	Penghu islands	Penghu airport
AA2	Suburban Hualien	Hualien airport
AA3	Urban Taipei	Taoyuan airport
AA4	Urban Taichung	Taichung airport
AA5	Urban Kaohsiung	Tainan airport

Table 4 gives the information gathered for the ramp space in each AA. For AA1, there is no room for airport expansion, so no fixed-wing aircraft can land there. Other airports are suitable to offload commodities (MOTC, 2014). According to the ROC Ministry of Transportation and Communication (MOTC) annual report, the international airport at AA3 has large ramp areas that could be used in a disaster (MOTC, 2014). Tainan military airport is also a large airport that can be used for AA5 (MOTC, 2014). Airports in AA2, AA3, and AA4 are farther away from downtown cities so their ramp space expansion costs are assumed to be lower.

Table 4. Ramp space at AAs.

Affected area	Initial capacity (ft^3 x 1000)	Max. expansion (ft^3 x 1000)	Expansion cost ($/ ft^3 x 1000)
AA1	0	0	0
AA2	25	100	10,000
AA3	50	100	10,000
AA4	20	80	10,000
AA5	20	60	15,000

Table 5 shows the population for each AA, taken from the National Development Council (NDC). Population is used later in this thesis to set up different scenarios of affected EP, AP, and DP as fractions of the total population. Each fraction will represent an estimate of the elderly population and people in the AA without a vehicle (NDC, 2014).

Table 5. Population in each AA.

Affected	Population
AA1	228,110
AA2	558,220
AA3	10,515,960
AA4	5,510,448
AA5	6,591,866

2. Data for Relief Locations

The MND has helped local governments with natural disaster prevention and relief for years, and past experiences show there are several locations that can be used for disaster relief (MND, 2011). Figure 11 shows the subset of these locations that constitute the RLs in this thesis. Table 6 provides the names and descriptions of these sites.

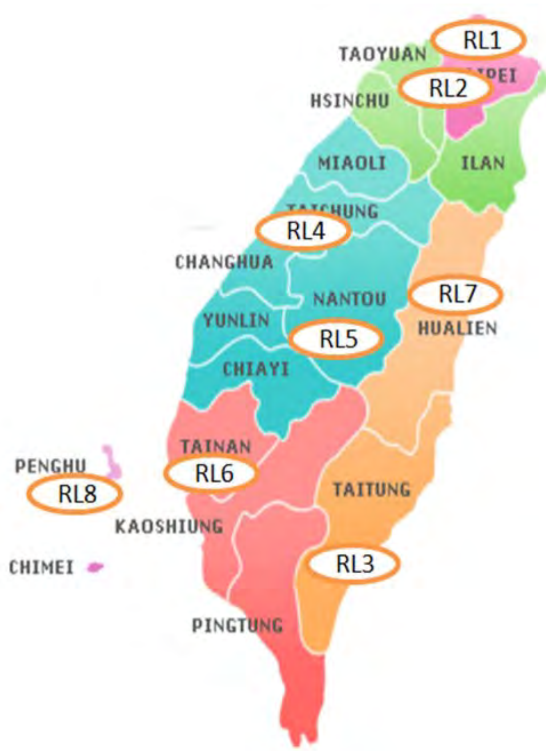


Figure 11. Geographical locations of the eight RLs selected for this thesis.

Table 6. RL names and descriptions.

Relief location	**Name**	**Description**
RL1	Taipei Hospital	Large hospital
RL2	Daan Forest Park	Large county fairgrounds
RL3	Taitung Hospital	Local hospital
RL4	Taichung Hospital	Local hospital
RL5	Nantou Hospital	Large hospital
RL6	Tainan Municipal Hospital	Large hospital
RL7	Buddhist Tzu Chi General Hospital Emergency Room	Large hospital
RL8	Tri-Service General Hospital Penghu Branch	Military hospital

Warehouse capacities determine the amounts of commodities that can be prepositioned at RLs prior to a disaster. This includes using spaces that are not initially designed for storing commodities (MND, 2011), all of which can be further expanded as shown in Table 7. RL1, RL3, RL4, RL7, and RL8 do not have initial capacity available. We assume warehouses are filled with 10-foot storage containers.

Table 7. Warehouse capacity and expansion costs.

Relief location	Initial capacity (ft^3 x 1000)	Max. expansion (ft^3 x 1000)	Expansion cost ($\$/ft^3$ x 1000)
RL1	0	150	300,000
RL2	150	780	100,000
RL3	0	100	300,000
RL4	0	100	250,000
RL5	150	750	200,000
RL6	150	600	200,000
RL7	0	100	300,000
RL8	0	100	250,000

The actual warehouse storage capacity at RL2 and RL8 is more than indicated, but because these are active military bases or airfields, only a fraction of their warehouse space is assumed to be available for storage of commodities. The other RLs are hospitals and have limited amount of space to expand as storage.

Each RL also has the ability to house large numbers of people. The MND has assessed the parking and hard surface area at these RLs and has determined possible mass housing locations. For this thesis, it is assumed that 30% of the parking and hard surfaces at these RLs can be used for mass housing and shelter. Using an estimate of 40 square feet of shelter space needed per person (American Red Cross, 2002), the DP initial capacities and potential expansion for each RL are indicated in Table 8.

Table 8. Shelter capacity and expansion costs.

Relief location	Initial capacity (persons)	Max. expansion (persons)	Expansion cost ($/persons)
RL1	14,968	2,000	1,000
RL2	1,450	500	1,000
RL3	800	200	1,000
RL4	1,332	500	1,000
RL5	3,000	500	1,000
RL6	2,000	500	1,000
RL7	0	200	1,000
RL8	100	200	1,000

Each RL also has a capacity to house healthcare personnel in support of the EP, as shown in Table 9. Healthcare personnel are doctors, nurses, and other administrative personnel that can assist the EP.

Table 9. Healthcare facility capacity and expansion costs.

Relief location	Initial capacity (healthcare personnel)	Max. expansion (healthcare personnel)	Expansion cost ($/healthcare personnel)
RL1	600	200	1,500
RL2	0	0	0
RL3	200	50	1,500
RL4	400	100	1,500
RL5	0	0	0
RL6	0	0	0
RL7	150	50	1,800
RL8	150	50	1,800

This thesis assumes a ratio of 10 patients per doctor over the 72-hour post-disaster period. For example, from Table 7, we assume that RL3 initially has 200 medical personnel available to treat up to 2,000 EP, and that up to 50 more can be prepositioned (i.e., available on call) at a cost of $1,500 per healthcare provider.

3. Data for Vehicles

In order to rescue the EP, deliver commodities to the AP, and transport the DP, vehicles are needed. This research considers the many different modes of transportation from multiple agencies that can be used to serve the three needy populations. Our test case assumes the transportation assets and data shown in Tables 10 and 11. All these data have been compiled during multiple interviews, electronic communications, and fact sheets provided by different agencies, as described below.

For example, in 2010, 31.5 million passengers rode on public transportation in the Taiwan region. In a disaster, local buses and shuttles would be very useful in transporting displaced people from AAs to RL shelters. The bus and shuttle information has been acquired from the MOTC (2014).

Table 10. Vehicle capacity and expansion costs.

Vehicle type	Availability (# of units)	Max. expansion (# of units)	Expansion cost ($/ft^3 x 1000)
Bus	25	250	5,000
Shuttle	25	500	8,000
HMMWV	15	50	40,000
C130	15	20	80,000
C17	5	8	175,000
EC225	3	3	0
UH-60	15	20	200,000
Truck 10.5 tons	25	20	19,000
Truck 0.75 tons	30	40	15,000
Ambulance	35	40	500,000

Each local government owns vehicles, such as buses and shuttles, which can also be used in disaster relief. Both buses and shuttles can transport commodities to the AP

and also transport DP back to RLs, but trucks can only transport commodities to the AP. Local hospitals have to provide ambulances during disasters for assisting in the rescuing of EP.

Table 11. Vehicle characteristics.

Vehicle type	Commodities (ft^3 x 1000)	Survivors capacity (persons)	Workers capacity (persons)	Displaced capacity (persons)	Availability (hours)	Operation range (hours)
Bus	0.6	15	5	40	68	12
Shuttle	0.4	10	40	40	68	12
HMMWV	0.2	3	0	0	72	6
C130	5.0	0	90	90	60	5
C17	8.0	0	100	100	60	5
EC225	2.0	4	8	24	48	5
UH-60	3.0	6	3	5	48	5
Truck 10.5 tons	1.5	15	5	0	72	8
Truck 0.75 tons	1.0	5	5	0	72	12
Ambulance	0.0	4	0	0	62	8

The MND has many assets that could be used during a disaster, especially C17s, C130s, and HMMWVs. Since these assets are in constant flux, we assume that five C130s, eight C17s, and 30 HMMWVs are initially available. We assume the MND will provide its available helicopters, such as EC225s and UH-60s, to assist in the rescue of the EP during a disaster (MND, 2011)

The vehicles have associated travel times from each RL to each AA. These times are a function of their speed and the distance covered. For simplicity, we use a central location in each AA to calculate the distance and travel time between given RLs and AAs. This is how we adapt the POM model.

4. Scenario Data

Typhoon disasters can cause different damage depending on their intensity and crossing path. In this thesis, we evaluate five possible base scenarios with an increasing number of AAs. The EP, AP, and DP are a different percentage of the population of the

AA. Depending on the scenario, different AAs are involved. The EP, AP, and DP are different percentages of the population of an AA, but we assume each AA has the same percentage. Depending on the scenario, different AAs are involved. Most of the population in the AAs is expected to evacuate before the typhoons cross due to the possible flood warning, rising rivers, and continued rain. The population that is left and needs assistance is the focus of these scenarios.

We model a situation in which a typhoon is approaching from the eastern side of Taiwan. This typhoon is expected to devastate a path from eastern Taiwan toward the western side of Taiwan and its outlying islands. The possible five regions are as follows: urban Kaohsiung (area 4), urban Taichung (area 5), urban Taipei (area 3), suburban Hualien (area 2), and Penghu islands (area 1). Each of the five regions is impacted with decreasing intensity, respectively, and each region is also an AA.

First-stage decisions, like deciding whether to build new medical facilities or warehouses, are "strategic decisions that must be implemented well before a disaster strikes" (Salmeron & Apte, 2009). In other words, they are long-term planning decisions that are made prior to the need for receiving requests for assistance for any particular storm. Other first-stage decisions include expansion for injury transfers, commodities, and ramp space. Second-stage decisions (commodities delivered, unmet demand, and number of injury transfers, rescue workers transferred, transportation expansion, and number of trips) are made after the disaster takes place. Specific scenario and affected area descriptions are shown in Figure 12, where "potential survivors" is the number of people in the EP. We refer to scenarios 1 through 5 as $\omega_1,\ldots, \omega_5$, respectively, in the remainder of this document.

Scenario 1 is a typhoon affecting all five areas severely. In scenario 2, areas a2, a3, a4, and a5 are affected moderately. Scenario ω_3 has the typhoon affecting eastern Taiwan, a2, a3, and a5. In scenario ω_4, the storm is severely affecting a2 and moderately affecting city area a3. For the final scenario, ω_5, the typhoon only affects a2, and there are no demands for assistance for the transport of people or commodities.

Scenario	Description	Affected Area
1. Including outlying islands (Kim-men area)	• AA1 has less resources, can not access resources from Taiwan island	• All five AAs (Potential survivors: 15,050)
2. Entire main island	• Categories 4, 5, 7, and 8 • Easy relief provider location (RL) expansion • More aircraft available	• AA2, AA3, AA5 and AA4 (Potential survivors: 12,050)
3. City and Urban (Central Taiwan)	• Categories 3 and 4 • More aircraft available	• AA2, AA3 and AA5 (Potential survivors: 11,050)
4. City (Northern Taiwan)	• Category 1, 2, and 3 • High intensity population • Difficult to expand	• AA2 and AA3 (Potential survivors: 4,150)
5. Urban (Eastern Taiwan)	• Category 6 • Limited resource access from western Taiwan	• AA2 (Potential survivors: 450)

Figure 12. Scenarios and descriptions selected for analysis.

J. ASSUMPTIONS

The overarching assumption in our analysis is that in the most extreme scenario, the typhoon has an impact similar to that of the extreme Typhoon Morakot in 2009. The five AAs are selected based upon geographic similarities to the five MND assigned areas of operation (AOs). The population impact and demand data are scaled with the same ratio corresponding to each area. We also assume that if scenario 1 occurs, the MND will be requested to provide the same amount of support that was provided following Typhoon Morakot. Local governments are also assumed to be providing support to share the workload. The $300 million budget is comparable to the budget that was spent by the Taiwan government for Typhoon Morakot (NAPHM, 2011). The analysis addresses how that support mission should be allocated to each AA.

We focus on modeling only the emergent phase of the relief effort and assume that each active military base from the five AOs is given the task of responding to the disaster corresponding to the closest AA. The time horizon for the relief effort from

MND assets is within 72 hours, with assets providing support as soon as they arrive on RLs. The manned aircraft receive waivers to allow aircrews to operate for the maximum allowable time, with skilled operators taking shifts. It is also assumed that no maintenance or downtime is required for the means of transportation.

We assume most military resources are from the Army, so there is no sealift assistance and no helicopters from the Navy or others. Also, airdrops of relief supplies are assumed not to be possible. We also assume no assistance from other countries will be requested.

K. BASE CASE RESULTS

We use the POM as developed by Salmeron and Apte (2010), with additional relief workers constraints that limit the maximum number of relief workers available at each RL. We also use the same implementation in the General Algebra Modeling System (GAMS; 2011) and the GAMS/CPLEX solver. The runs have been conducted on a Dell Latitude XT2 laptop with 4 GB of RAM and an Intel Core Due processor, partitioned to contain a Windows 7, 32-bit operating system. In each run, the dimensions of the model are approximately 37,000 constraints and approximately 83,000 variables, of which 23,000 are integer variables. A typical run of any of the above cases takes approximately one minute with a 5% optimality gap.

In the following runs, the survival rate and budget levels are varied to analyze how the budget is allocated to the number of relief workers. In Figure 13, we plot the expected number of workers versus the budget for three different survival rates, where the survival rate represents the proportion of EP people who will eventually recover if they are rescued. Eleven different budgets are used, ranging from $0 to $10 million.

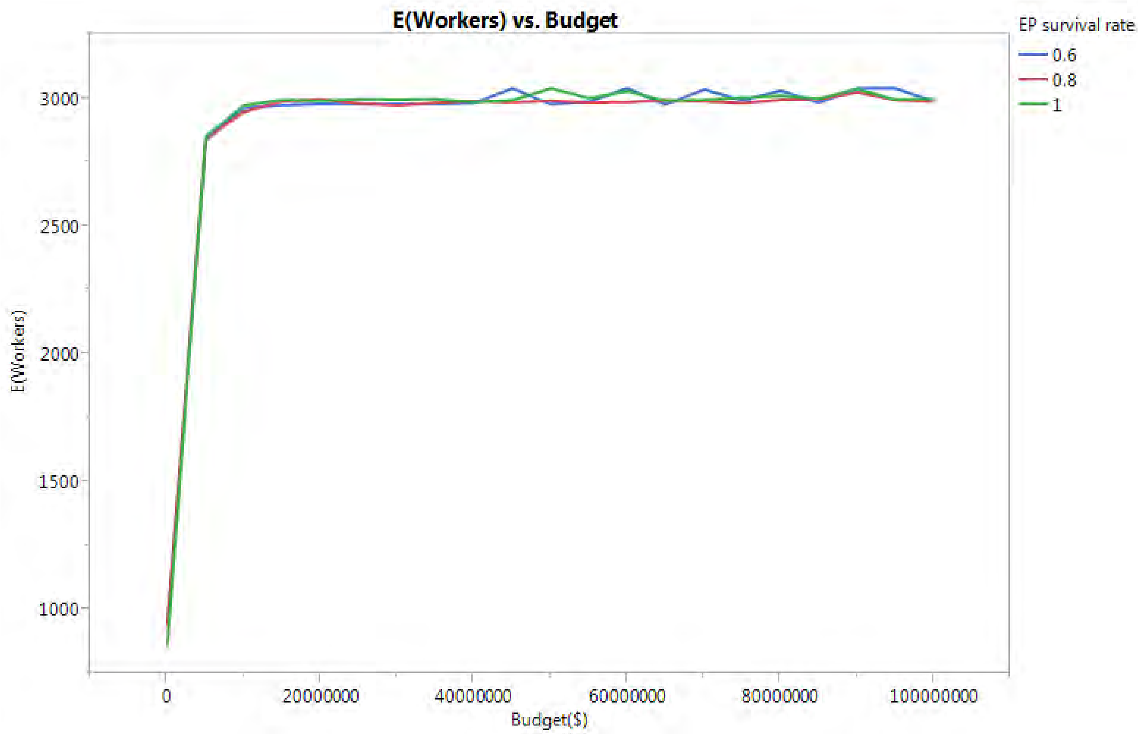


Figure 13. Expected total deployed relief workers versus budget.

From Figure 13, the budget ranges from \$0 to \$100 million, while EP survival rates of 60%, 80%, and 100% lead to very similar numbers of the total relief workers. For budgets of \$10 million or more, the number of total workers remains approximately constant at around 2,750 people.

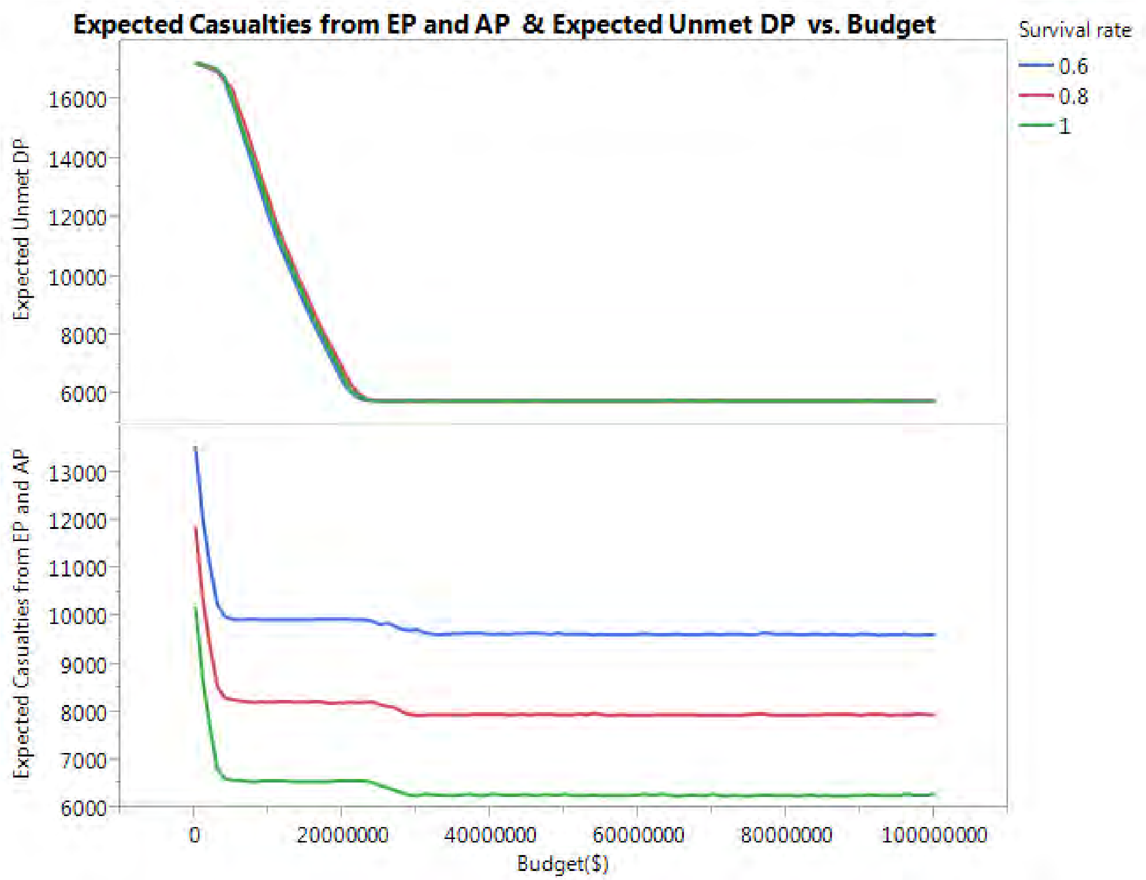


Figure 14. Expected unmet DP versus budget (top). Expected casualties from EP and AP versus budget (bottom).

Figure 14 shows the average expected unmet DP versus budget and the average expected casualties from EP and AP versus budget from all scenarios. The expected unmet DP decreases linearly as the budget increases to $25 million and remains constant as the budget increases beyond $25 million. Observe that the expected unmet DP is approximately equal for the three survival rates. Expected casualties from EP and AP drop sharply when the budget is between $0 and $5 million. It remains constant as the budget increases to $25 million before decreasing slightly. Expected casualties from EP and AP taper off as the budget increases beyond $30 million. This trend applies to all survival rates, with higher survival rates resulting in lower expected casualties from EP and AP.

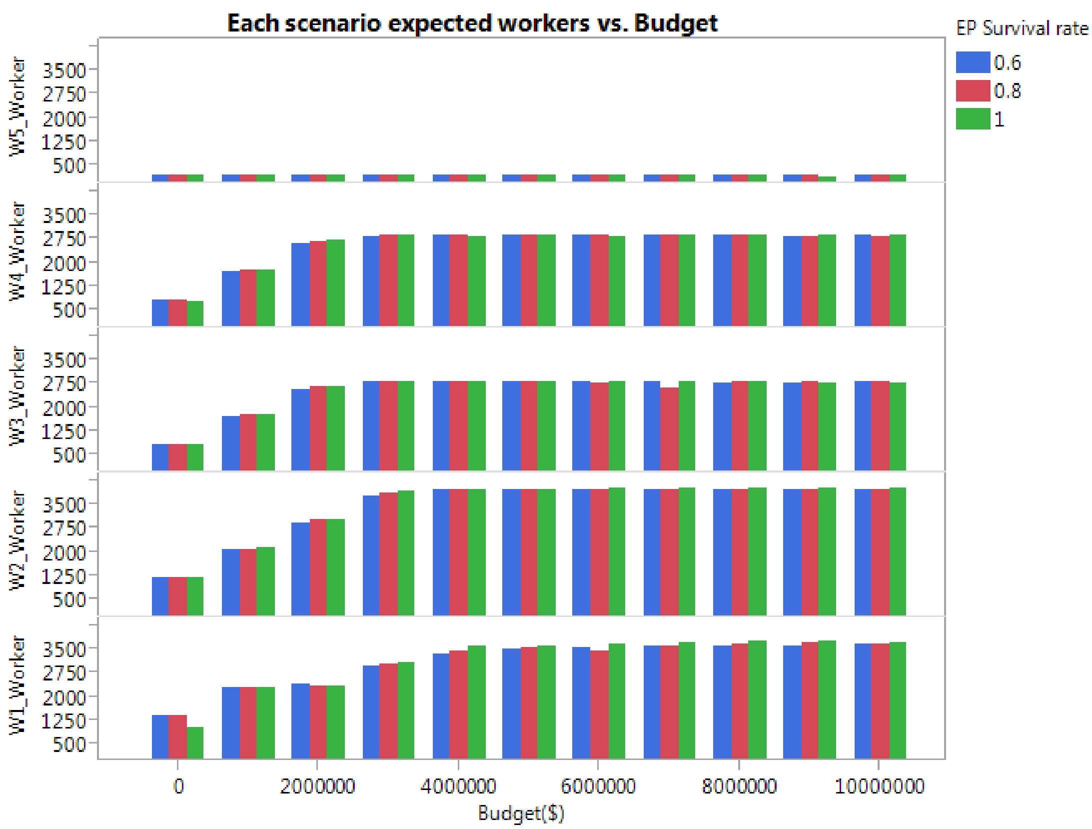


Figure 15. Expected total deployed relief workers versus budget, by affected area.

The individual scenario outputs of Figure 15, running smaller budgets ranging from \$0 to \$100 million, shows that more workers are deployed when more AAs are involved. In scenario 5, with only area 2 affected, the same number of workers is deployed regardless of the total budget.

We further analyze the relationship between the expected uses of the budget and the given budget ranges from \$0 to \$100 million. The result is shown in Figure 16. After the \$50 million budget is spent, the 60% survival rate uses more of the available budget than other survival rates. This may be because the budget is a constraint, rather than part of the objective function; GAMS stops once it finds a feasible solution that satisfies the budget constraint, but that might not be a unique solution. Figure 17 shows us the expected unmet commodities versus budget; it also shows that after \$50 million is available, the amount of unmet commodities stays the same.

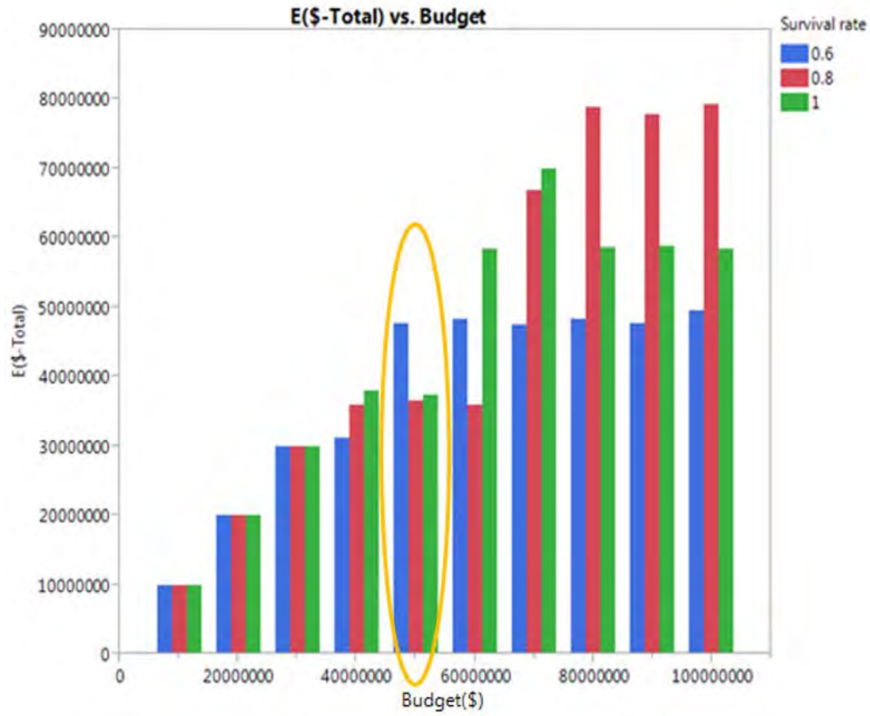


Figure 16. Expected total cost versus budget.

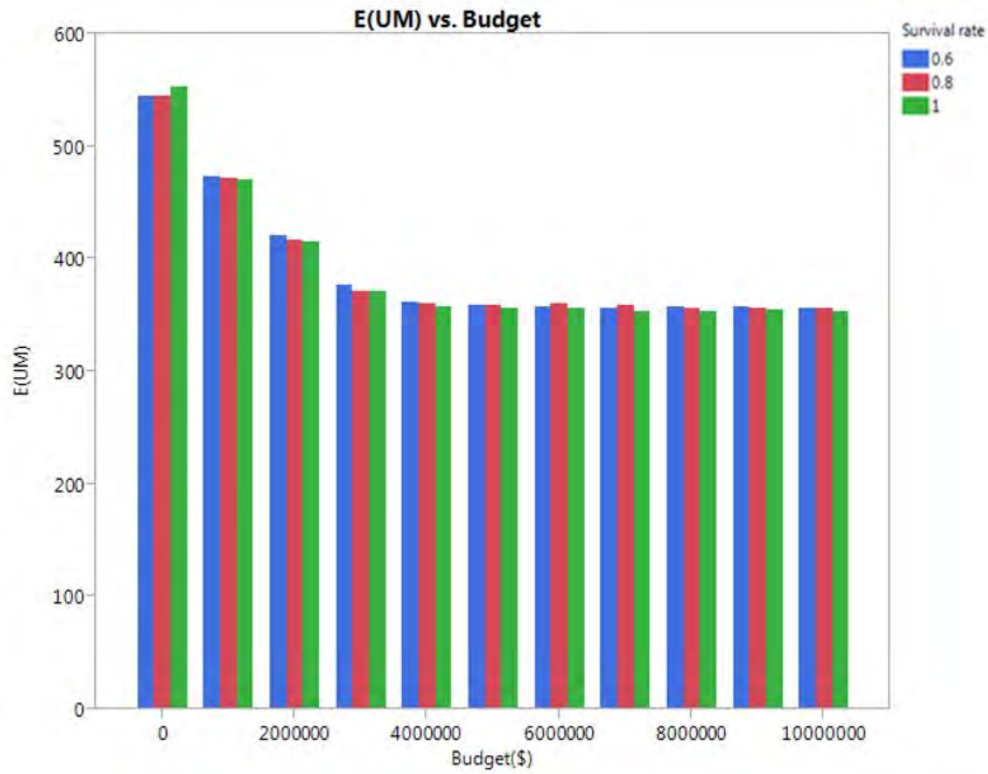


Figure 17. Expected unmet commodities versus budget.

The observation that the objective function values stabilize after the budget reaches $30 million, while the costs continue to rise, indicates that there may be multiple optimal solutions, because there is no incentive in the POM to save money. Table 12 shows the output for three survival rates, 60%, 80%, and 100%, using a $50 million budget and a penalty multiplier of 18.5.

Table 12. Base case summary results with $50 million budget.

EP Survival Rate (%)	60	80	100
Potential casualties (persons)		8,350	
Expected unmet EP (persons)	3,457	1,675	7
Expected EP who will die even if rescued	3,340	1,670	0
Calculated casualties rescued rate: (1-(Expected unmet EP/Potential victims))*100%	58.5%	79.9%	99.9%
Potential commodities needed ($ft^3 \times 1000$)		639	
Expected unmet commodities ($ft^3 \times 1000$)	335	339	341
Calculated commodities met rate: (1-((Expected unmet commodities/Potential commodities needed))*100%	45.5%	44.9%	44.6%
Potential workers needed (persons)		4,585	
Expected deployed workers (persons)	3,045	2,995	2,985
Calculate workers assigned rate: (Expected deployed workers/Potential workers needed)*100%	66.4%	65.3%	65.1%
Given budget ($)		50,000,000	
Expected total cost ($)	47,797,200	46,457,240	44,596,820
Calculate budget used rate: (Expected total cost/ Given budget)*100%	95.5%	92.9%	89.1%
Total healthcare facility expansion cost ($)	2,733,996	1,280,731	2,400
Total ramp expansion cost ($)	3,700,000	3,700,000	3,700,000
Expected total transportation expansion cost ($)	203,200	135,240	296,820

This table shows that the unmet EP is only slightly higher than we would expect base on the EP survival rate. Also, the highest survival rate does not occur at the highest cost. The ramp expansion cost seems to be the same after a certain budget is reached, and the total number of workers actually decreases after the survival rate gets above a certain

level, but further investigation is needed before deciding what expansions are truly beneficial. In order to gain more insights, we use DOE in the following analysis.

II. DESIGN OF EXPERIMENTS

There are many different factors to be considered in the POM model. With a limited time and amount of computer resources to complete this study, an efficient design of experiments (DOE) is critical. Using a well-structured DOE, an analyst is able to develop a basic understanding of the system (Kleijnen et al., 2005). Applying a proper design, many aspects of a complex model can be studied with high fidelity and in exponentially less time than looking at all possible combinations of factors. This includes identifying how the factors affect the response, how the factors interact with each other, and how sensitive the system is to variations in factors. Our approach is similar to that of Gardner (2015), who also uses DOE to explore a variant of POM for disaster relief.

A. METHODOLOGY

The overall DOE approach is shown in Figure 18. In this experiment, several GAMS parameters are selected as factors: the maximum available relief workers at relief locations, the maximum budget, the penalty incurred when workers are unable to transport commodities, the survival rate of EP, and the probabilities of occurrence of potential scenarios. A NOB design for discrete and categorical factors (Vieira et al., 2013) is used to vary the discrete and continuous input data parameters of the POM. This design can be found on the SEED Center website (http://harvest.nps.edu/). Our experiment uses 512 design points to explore 32 factors.

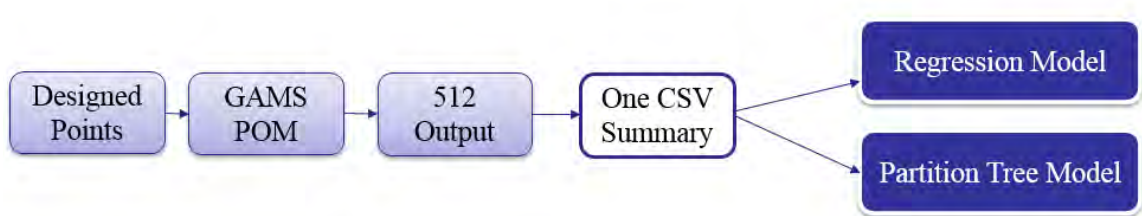


Figure 18. DOE approach.

Once a design is created, there is a multi-step process to compile the data for analysis. First, the cells in the design spreadsheet are copied into a Comma Separated Value (CSV) file. Each of the 512 rows of the CSV file is a design point and a separate POM problem instance. Second, a script written in the Ruby programming language (Ruby, 2015) is run from the command line; it pulls the values from the CSV file row by row and constructs 512 sets of new GAMS files from the POM base case model, one set for each design point. To automate the process of running all the GAMS files, a Windows batch file (BAT) is used to call on GAMS to solve each version of the model. The BAT file creates a new directory for each run to hold output, and one of the outputs is a summary CSV file, 512 individual summary in total at this point. Fourth, we concatenate these 512 individual CSV summary files into one combined CSV summary file with separate rows for each design point. The end result is a dataset that is suitably configured for further regression model and partition tree model analysis.

1. Factors and Factor Ranges

a. Budget, Survival Rate, and Penalty

Table 13 shows the factors and ranges that were varied during the experiment. Based on the base case output, we ran the budget from \$1.5 million to \$6 million. We varied the EP survival rate range from 60% to 100%. In this case, higher penalties increase the requirement to meet demand full commodities by the AP, rather than EP.

Table 13. Budget, survival rate, and penalty factors and ranges.

Factor	Type	Level Range
Maximum Budget	Continuous (dollars)	\$1.5–6 million
EP Survival Rate	Continuous (%)	60 –100%
Penalty	Continuous (%)	50.5–80.5%

b. Scenario Probabilities

Table 14 contains the design probability of each scenario. According to the historical typhoon data, ω_3 occurs more often than others. We set ω_3 as the baseline for the design. We vary probabilities for three other scenarios as factors over lower ranges; in

these cases, we know the other probabilities would not have higher probability than ω_3. To make sure the sum of total probability equals one, we set ω_5 equal to one minus the sum of other scenario probabilities. Note that ω_5 ranges from 0.03 (if ω_2–ω_4 are all at their highest values) to 0.42 (if ω_2–ω_4 are all at their lowest values), so it can be higher than ω_3. This experiment uses a full factorial design, where the design range and the fraction values are taken from the NOB table.

Table 14. Scenario probability factors and ranges.

Factor	Design Range
Probability ω_1 (P_{ω_1})	$P_{\omega_1} = \{1 - \sum_{i=2}^{5} P_{\omega_i}\}$
Probability ω_2 (P_{ω_2})	$[0.1, 0.15]$
Probability ω_3 (P_{ω_3})	$[0.28, 0.42]$
Probability ω_4 (P_{ω_4})	$[0.1, 0.15]$
Probability ω_5 (P_{ω_5})	$[0.1, 0.15]$

c. Available Relief Workers

We look at 25 factors that represent the numbers of relief workers available to handle commodities at each AA under each scenario, and vary their values between plus and minus 20% of the base case values. The factors and design ranges are shown in Table 12; we use a separate column from the NOB spreadsheet for each factor. This experiment focuses on helping find suitable numbers of military relief workers to deploy, while ensuring that the relief efforts are effective. This means we may end up deploying fewer workers than are available.

Table 15. Available relief worker factors and ranges.

Scenario, ω	AAs	Base Case (persons)	Factor Range (persons)
ω_1	AA1	300	[240, 320]
	AA2	2,000	[1,600, 2,400]
	AA3	2,000	[1,600, 2,400]
	AA4	2,000	[1,600, 2,400]
	AA5	2,000	[1,600, 2,400]
ω_2	AA1	50	[40, 60]
	AA2	2,000	[1,600, 2,400]
	AA3	2,000	[1,600, 2,400]
	AA4	2,000	[1,600, 2,400]
	AA5	2,000	[1,600, 2,400]
ω_3	AA1	50	[40, 60]
	AA2	2,000	[1,600, 2,400]
	AA3	2,000	[1,600, 2,400]
	AA4	50	[40, 60]
	AA5	2,000	[1,600, 2,400]
ω_4	AA1	50	[40, 60]
	AA2	2,000	[1,600, 2,400]
	AA3	2,000	[1,600, 2,400]
	AA4	50	[40, 60]
	AA5	50	[40, 60]
ω_5	AA1	300	[240, 320]
	AA2	50	[40, 60]
	AA3	50	[40, 60]
	AA4	50	[40, 60]
	AA5	50	[40, 60]

The NOB design includes a total of 32 factors: one for the budget, one for the EP survival rate, one for the penalty rate, four for the probabilities, and 25 for the required numbers of workers. The final design is nearly orthogonal: The highest correlation between any pair of factors is very low, 0.005.

2. Output Measures

The goal here is not just finding a solution that maximizes or minimizes the metric of interest, but a solution that also looks at the variability of that optimal solution. There are several outputs in which we are interested, including the expected number of relief workers deployed, the expected EP and AP casualties under a given scenario, and the expected unmet demand for the transfer DP.

B. ANALYSIS

This section analyzes the output of the experiment and points to a preferred set of conditions and actions that can be implemented to help us to find good values of three output measures. The analysis is performed using the JMP statistical package. The data are analyzed using descriptive statistics, linear regression, and partition trees, to explain the relationship between the factors of interest and their effect on the three measures of effectiveness. We treat all values as continuous numbers in the JMP analysis.

1. Expected Number of Deployed Workers

We will let E[Workers] represent the expected number of deployed relief workers for a single design point, which is less than or equal to the number of available workers for that same design point. E[Workers] ranges from 50 to 2,500 by scenario across the 512 design points. Figure 19 shows a summary of the regression model predicting the expected number of deployed relief workers. With a resulting R-square over 0.97, the most influential factor affecting the expected number of deployed workers is the maximum budget. The probability of each scenario also has a significant impact on results. Factor a3_w4 in Figure 19, which represents a typhoon crossing northern Taiwan, is more significant than the analogous variables for other scenarios.

Summary of Fit

RSquare	0.977076
RSquare Adj	0.976524
Root Mean Square Error	36.00789
Mean of Response	2647.791
Observations (or Sum Wgts)	512

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
maxbudget	0.0001391	1.225e-6	113.52	<.0001*
(maxbudget-3750000)*(maxbudget-3750000)	-6.91e-11	1.07e-12	-64.77	<.0001*
pw5	-3169.61	54.89116	-57.74	<.0001*
pw3	-596.8386	39.15632	-15.24	<.0001*
(maxbudget-3750000)*(pw3-0.35)	-0.000331	0.00003	-11.05	<.0001*
(maxbudget-3750000)*(pw5-0.15)	-0.000421	4.028e-5	-10.46	<.0001*
pw4	-688.344	106.9895	-6.43	<.0001*
(a3_w4-2000)*(pw4-0.125)	1.4406476	0.458547	3.14	0.0018*
(maxbudget-3750000)*(pw2-0.125)	-0.000253	8.238e-5	-3.07	0.0022*
pw2	193.17571	106.4987	1.81	0.0703
a3_w4	-0.011737	0.00694	-1.69	0.0914
(pw3-0.35)*(pw5-0.15)	-1700.615	1281.39	-1.33	0.1851

Figure 19. Regression model for the expected number of deployed relief workers.

The regression produces a good fit to the data, but does not easily explain or provide a set of rules or guidelines for the commander to use. Another way to visualize the important factors in determining this model is through a partition tree. This method of modeling splits the data into groups so as to minimize the total sum of squares error (SSE). The factor and level of the factor for the split is chosen by the algorithm, based on which split maximizes the reduction in the total SSE. In other words, the data are partitioned into two groups according to which factors and levels explain the majority of the variation in the data. In JMP, the splits are controlled manually until the desired degree of accuracy is achieved or the resulting pool of data has reached a minimum required for further splits because of insufficient observations or insufficient variability in the response (Sall, Creighton, & Lehman, 2005).

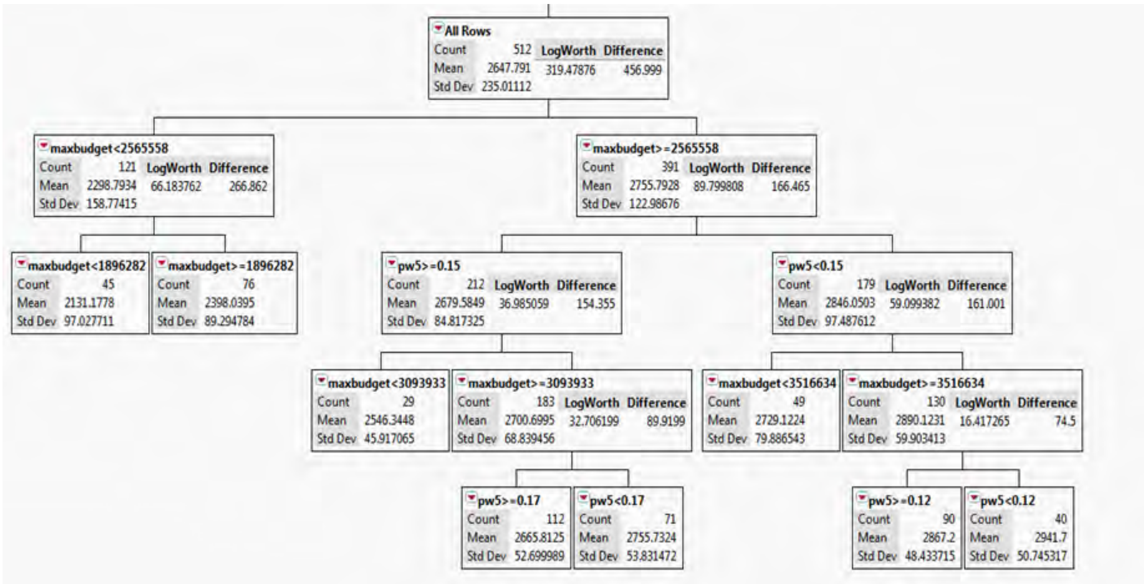


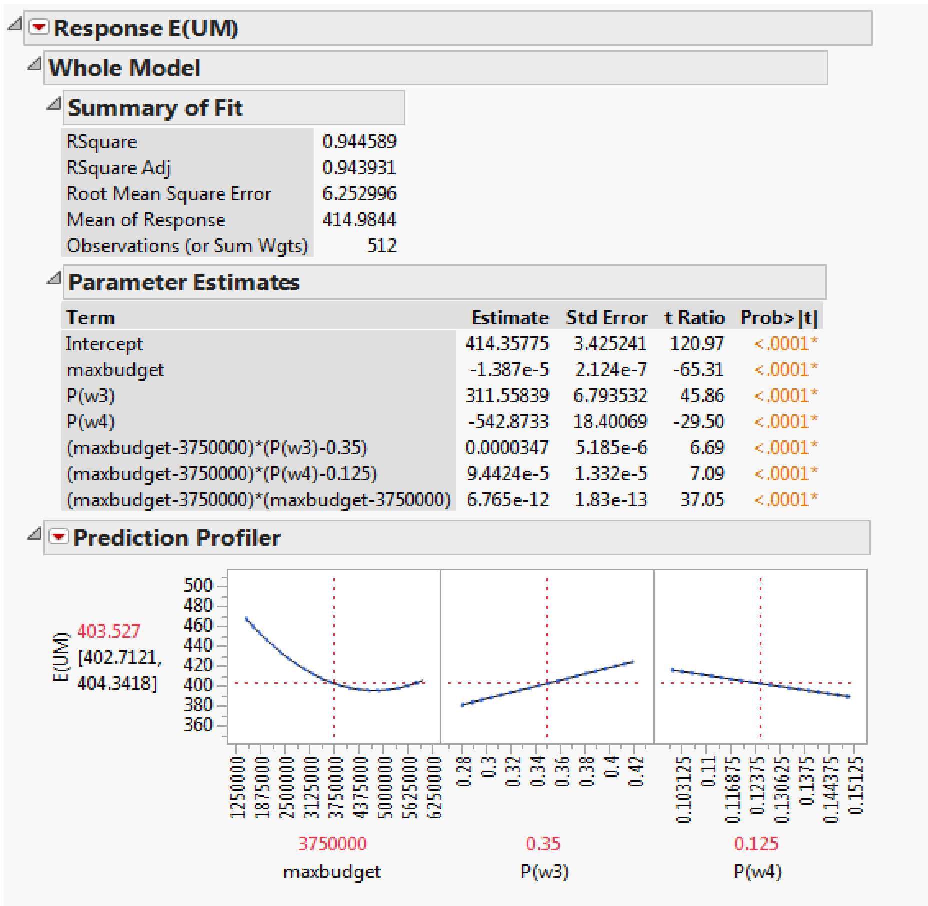
Figure 20. Partition tree for the expected number of deployed relief workers.

The partition of the predicted workers model is shown in Figure 20. This tree explains the majority of the variability in the data, with resulting R-square over 0.92 with only seven splits. The data used for the partition tree includes all 512 design points. The most influential factor in the partition tree model is the same as in the regression model—namely the maximum budget. For a given budget and assumed probability of occurrence of scenario ω5, the expected number of relief workers required can be estimated. For instance, if we know that we have a maximum budget of $35 million and the probability of scenario 5 is less than 0.12, then we should expect to deploy on average 2,942 people. Furthermore, for this leaf of the partition tree, the expected unmet casualties is 3,008 and the expected unmet commodities is 411.

2. Expected Unmet Commodities

Figure 21 shows a summary of the regression model predicting the amount of unmet commodities. With a resulting R-squared over 0.94, the most influential factor affecting the amount of unmet commodities is the maximum budget, and the probability of scenario ω_3 is the second most influential factor. Penalty and EP survival rate both have statistically significant impacts on results, but are of little practical importance, so

we have not included them in the model. The prediction profiler shows a tendency toward the same amount of unmet commodities as the budget surpasses the $50 million level.



Response E(UM)

Whole Model

Summary of Fit

RSquare	0.944589
RSquare Adj	0.943931
Root Mean Square Error	6.252996
Mean of Response	414.9844
Observations (or Sum Wgts)	512

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	414.35775	3.425241	120.97	<.0001*
maxbudget	-1.387e-5	2.124e-7	-65.31	<.0001*
P(w3)	311.55839	6.793532	45.86	<.0001*
P(w4)	-542.8733	18.40069	-29.50	<.0001*
(maxbudget-3750000)*(P(w3)-0.35)	0.0000347	5.185e-6	6.69	<.0001*
(maxbudget-3750000)*(P(w4)-0.125)	9.4424e-5	1.332e-5	7.09	<.0001*
(maxbudget-3750000)*(maxbudget-3750000)	6.765e-12	1.83e-13	37.05	<.0001*

Figure 21. Regression model for the expected unmet commodities.

A partial partition tree of expected unmet commodities model is displayed in Figure 22. After only six splits, we observe R-squared over 0.81; after 21 splits, we observe R-squared over 0.92. The important factors are the maximum budget, and the probability of scenario 3 or 4 occurring. Combining both model outputs, the impact factors are similar. In general, to obtain a better prediction of unmet commodities, we would like to know the budget constraints and the frequencies of scenarios 3 and 4.

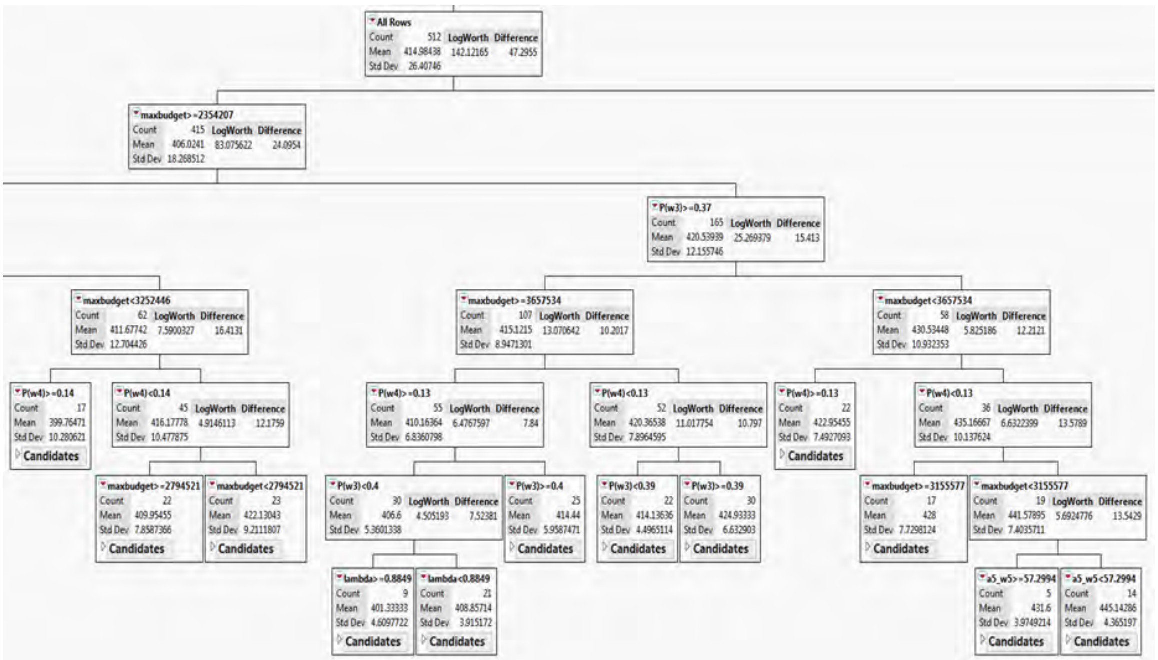


Figure 22. A partial partition tree for the expected unmet commodities.

3. Expected Number of Casualties

We observe more detailed information from the partition model than the regression model for this predicted number of casualties model. Figure 23 shows the partition tree of the expected casualties model. With R-squared over 0.94 after five splits, the only important factor is the EP survival rate. We can get the expected casualties as low as 247 people if we set our EP survival rate higher than 95%. However, if we set up the EP survival rate less than 71%, then the average expected casualties can be up to 3,300 people. It is a significant outcome that a 20% change in the EP survival rate causes an almost 3,000-person difference in the expected number of casualties.

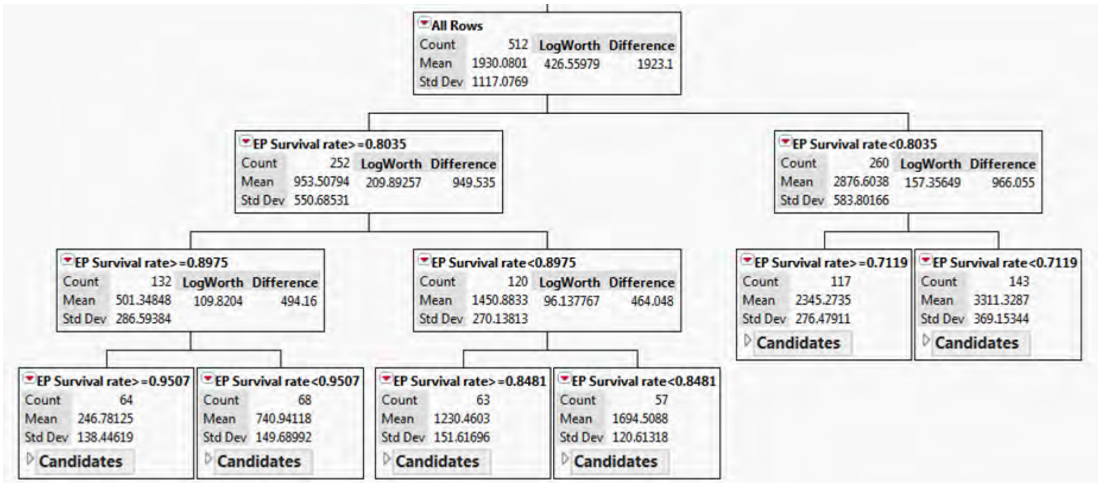


Figure 23. Partition tree for expected casualties.

Conducting DOE on an optimization model provides insights that are otherwise not observed with a stochastic optimization model like POM. Sensitivity analysis for an optimization model cannot always allow a focused investigation of how specific input data directly affect the output in the way DOE permits. Our series of models shows which parameters have more influence over the POM solution and objective values. Such analysis provides disaster relief planners with valuable guidance.

As we explore the impact of the parameters and their assigned ranges on the solution, we can see the changes in the output. Table 16 shows the comparison between different analysis model approaches. We can see that the DOE approach is necessary to account for a wider range of possibilities and has the opportunity to provide more realistic results. DOE on POM permits specific parameters to change as factors for different levels of interest change. This gives us the opportunity to focus on specific parameters for a better prediction. Of course, when we are interested in several measures of effectiveness at the same time, we may need to make trade-offs.

Table 16. Analysis model output comparison for three measures of effectiveness.

Measure of effectiveness \ Analysis model	Regression model key factor and predicted range	Partition tree model key factor and predicted range
Number of Deployed Workers E(Workers)	Budget level, $P_{\omega_2}, P_{\omega_3}, P_{\omega_4}$, Number of workers deployed at AA3 in scenario 4. [1997 , 3070] (persons)	Budget level, P_{ω_4} [2130 , 2830] (persons)
Number of Casualties E(US)	EP survival rate, $P_{\omega_2}, P_{\omega_3}, P_{\omega_4}$ [12 , 3848] (persons)	EP survival rate [247 , 2870] (persons)
Unmet Commodities E(UM)	Budget level, $P_{\omega_3}, P_{\omega_4}$ [360, 540] ($ft^3 \times 1000$)	Budget level, $P_{\omega_3}, P_{\omega_4}$ [380 , 453] ($ft^3 \times 1000$)

C. DISCUSSION OF FIRST-STAGE DECISION VARIABLES

For a better understanding of whether available relief workers are used efficiently, we compute the available worker usage percentage from our summary CSV file. Table 17 shows each scenario's summarized outcome.

Table 17. Available workers usage percentage.

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Historical data (2010-14)
Average number of available workers	8300	8050	6100	4150	500	40945
Average actual number of workers deployed	3266	3771	2788	2812	206	3871
Usage percentage (available /expect x %)	39%	47%	46%	68%	42%	9%
Average usage	48%					

First, we calculate the average percent usage by finding the scenario averages of all 512 design points. For each scenario, we divide the average actual number of workers deployed by the average number of available workers. We compare the result with worker usage information from 13 typhoons between 2011 and 2014. Across our scenarios, the average available worker usage is 48%. In reality, only 9% of available workers were actually used during the 13 typhoons. From personal experience, the top line of the historical data column in Table 16 represents the total personnel who were activated to provide 24-hour coverage. The boxplot of each scenario's available worker usage rate is shown in Figure 24.

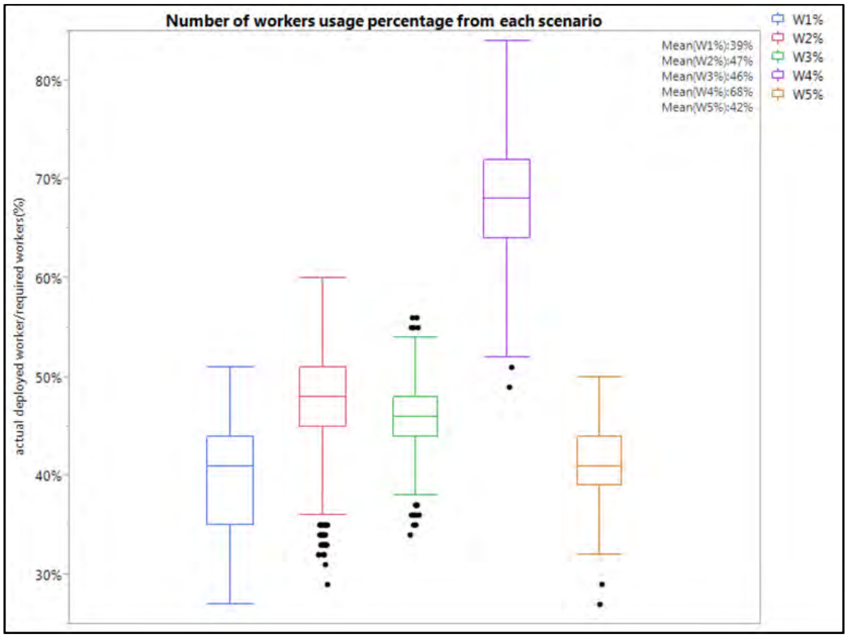


Figure 24. Available worker usage rate for each scenario.

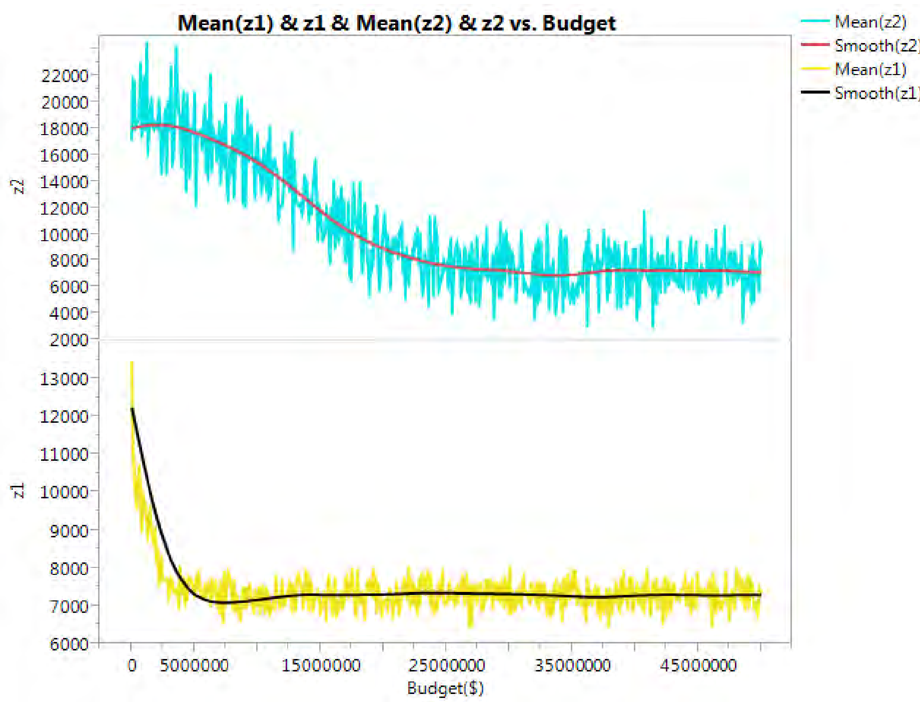


Figure 25. DOE output: Expected unmet DP versus budget (z2). Expected casualties from EP and AP versus budget (z1).

To better visualize the trends of expected casualties from EP and AP and expected unmet DP, we ran a second designed experiment using a 100% EP survival rate and a constant penalty ratio of 18.5%. As variations in expected unmet DP and expected casualties from EP and AP are observed to occur between $0 and $50 million, the DOE model will consider this budget range. Figure 25 shows the average expected unmet DP versus budget and the average expected casualties from EP and AP versus budget for all scenarios from the DOE results.

The number of deployed workers in this new experiment is also reduced from the base case by approximately 20%. The observations from the DOE output above agrees with the trend in Figure 14. The expected unmet DP initially decreases as the budget increases, but stabilizes around 8,000 as the budget increases beyond $25 million. The expected casualties from EP and AP drop sharply to 7,000, before stabilizing as the budget increases beyond $5 million. The output from this experiment suggests, once again, that disaster relief efforts can be effective without deploying all available workers or spending all the available budget.

We return to our original experiment in order to get better insight about expansion results. Our baseline output shows the majority of the budget was spent on ramp expansion. Interestingly, the 60% EP survival rate solution costs more than the nearly 100% EP survival rate case solution. This counterintuitive result could be caused by the objective function, which is designed to minimize casualties and not minimize funds expended. It is possible that among the multiple optimal solutions, there exists a solution with the same survival rate, but with a lower budget. This means the first-stage decisions, such as ramp space and healthcare facility expansion, are "feasible" rather than "optimal" with regard to the budget constraint (i.e., the budget constraint is not tight). Additionally, there is no incentive for the GAMS solver to choose first-stage decisions that reduce this budget. Ramp space expansion is a first-stage decision used as an example in Figure 26.

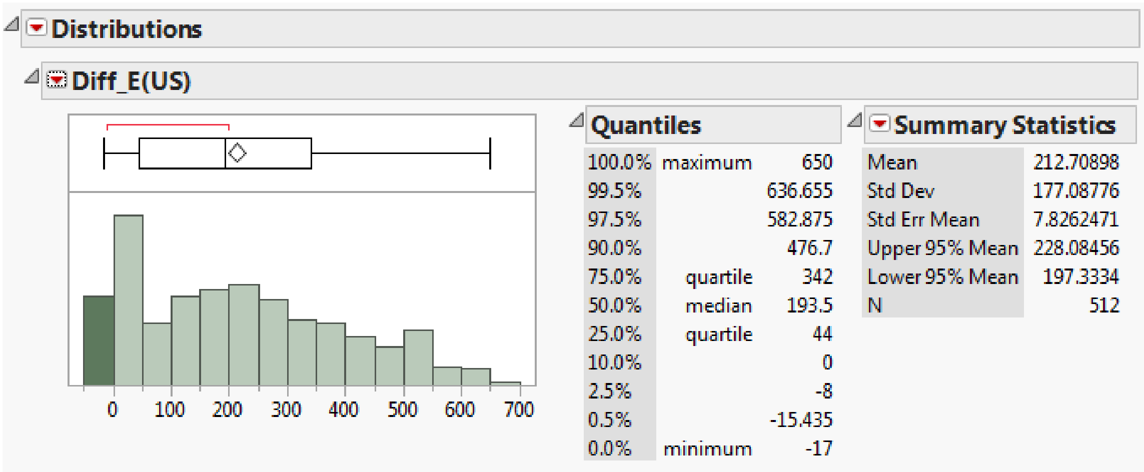


Figure 26. Difference in unmet casualties [(1-survival rate) x population] with ramp space expansion and unmet casualties with no ramp space expansion.

According to Figure 26, expanding ramp space would reduce the average unmet casualties by 213 people. As a first-stage decision, this relationship warrants additional study and has a measureable impact on second-stage decisions. The dark green represents either no casualty difference or increased casualties with ramp space expansion. Further research is needed to determine whether this behavior is present in similar two-stage stochastic optimization models for humanitarian assistance, such as those discussed in previous chapters. With additional analysis, it may be possible to determine whether the primary budget difference between each design point lies within the first-stage decision to expand or not to expand ramp space.

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III. CONCLUSION AND RECOMMENDATIONS

This thesis has demonstrated the use of POM to develop insights that can be of use to those planning typhoon disaster relief effects in Taiwan. We have considered a number of potential typhoon impact scenarios and allowed the POM to produce optimal solutions. As with any model, the results are dependent upon the assumptions that are made, and there are limitations. The assignments of probabilities for scenarios occurring adds some necessary uncertainty to the model. However, we can do more. Based upon the results of the experimental design, we can learn more about the potential situations that can arise with natural disaster response.

- The following are the conclusions and corresponding recommendations based on this research, we find that the estimated probability of scenario 3 and 4, in addition to the known budget limit, are important when predicting casualties. It is important to note that each scenario represents a different intensity of a crossing path category 2 typhoon. If a decision maker can have more accurate and current weather reports, he or she can refer to the path and intensity of typhoons while making rescue plans. Ideally, he or she can make more efficient allocation of resources to achieve the reduction in casualties, while not wasting human and relief resources. Continued cooperation between Taiwan MND and TWB is recommended.
- It is not necessary to spend as much money and deploy as many workers as we have in the past in order to get the best results. The outcome may become worse as the budget and the number of workers deployed increase beyond a certain level. From our analysis of the five scenarios, an average of 48% of available workers (only 9% of the historical number of workers) are deployed to reduce the number of casualties to a certain level.
- This POM model shows the decision maker the possible outcomes, such as the total cost of health facility expansion, ramp expansion, or transportation after entering the estimated value of key factors. We can run the model again with a smaller range applying to the known factors in order to provide us a better insight about other factors. In this case, the decision maker may be able to better estimate the number of workers needed in each AA responding to the predicted scenario.
- Further work is needed to determine how to identify good first-stage and second-stage expansion decisions, since POM can yield multiple optimal solutions. Adding a third objective function that seeks to minimize the expansion costs would be beneficial. The best alternative might involve a mix of optimization, simulation, and DOE methods.

The findings of this thesis are being provided to ROC MND. However, it is imperative to note that the results presented here depend entirely on the assumptions and input data (much of which had to be estimated). Changes to these assumptions and/or inputs could have significant impacts on the results. Finally, a Graphical User Interface (GUI) for data input and output would allow the MND to easily modify and evaluate new cases more efficiently.

APPENDIX. PREPOSITIONING OPTIMIZATION MODEL FORMULATION

This appendix describes the mathematical formulation for the POM model used in this thesis, as it appears in Salmeron and Apte (2010). There is one additional constraint added (constraint 8.3) in order to determine the number of troops deployed. The term vehicle used in the rest of this thesis is referred to as *Means of Transportation (MoT)* in this appendix.

Indices and Index Sets:

A Set of affected areas (AAs); $a \in A$

L Set of starting and drop off relief locations (RLs); $l \in L$

T Set of MoT (e.g., UH-1H aircraft, HMVV land-vehicle); $t \in T$

T_l Subset of MoT that can depart from (and drop off at) RL l

T^R Subset of MoT that require ramp space for delivery of commodities (aircraft assets)

Ω Set of disaster scenarios; $\omega \in \Omega$

Deterministic Parameters (units):

h_l^0 , $h_l^{\max}$, c_l^H Initial capacity for health personnel at RL l (healthcare providers), maximum capacity expansion (healthcare providers), and variable expansion cost ($ / healthcare provider)

s^H EP that one healthcare provider can handle (persons)

s_l^0 , $s_l^{\max}$, c_l^S Initial capacity for EP at relief location l (persons), maximum capacity expansion (persons), and variable expansion cost ($ / person). (These are based on the initial health personnel, maximum health personnel expansion, variable health personnel cost, and s^H)

r_a^0 , $r_a^{\max}$, c_a^R Initial ramp space capacity at AA a (ft^3×1000), maximum capacity expansion (ft^3×1000), and variable expansion cost ($ / ft^3×1000), respectively

m_l^0 , $m_l^{\max}$, c_l^M Initial capacity for commodities at RL l (ft^3×1000), maximum capacity expansion (ft^3×1000), and variable expansion cost ($ / ft^3×1000), respectively

$u_t^0, u_t^{\max}, c_t^U$ Initial number of units of MoT t (vehicles), maximum capacity expansion (vehicles), and variable expansion cost ($ / vehicle), respectively

d_l^0, $d_l^{\max}$, c_l^D Initial shelter capacity for DP at RL l (persons), maximum capacity expansion (persons), and variable expansion cost ($ / person)

$\bar{s}_t$ Capacity for EP of special MoT t (persons / vehicle × trip)

$\bar{m}_t$, $\bar{w}_t$ Capacities for commodities (ft^3×1000 / vehicle × trip) and relief workers (workers / vehicle × trip), respectively, of general MoT t

$\bar{d}_t$ Capacity for DP of general MoT t (persons / vehicle × trip).

h_t Available hours during the planning time for each unit of MoT t (hours / vehicle)

b Total budget allocated ($)

$\overline{w_a}$ Maximum number of workers deployable to area a (persons)

q Penalty for unmet commodities (i.e., q of the *stay-backs* that are assumed to perish per unit of unmet commodities) (persons / ft^3×1000)

α Relaxation level for the first objective when the second objective is optimized (fraction)

Scenario-Dependent Parameters (units), all under scenario ω:

m_a^ω Demand for commodities in AA a (ft^3×1000)

s_a^ω EP in affected area a (persons)

λ_a^ω Survival rate for EP rescued in affected area a (fraction)

d_a^ω Number of DP in AA a (persons)

h_{tla}^ω Trip time (hours) for MoT t to travel from RL l to AA a (hours / trip). (The same time is assumed from a to l, so only h_{tla}^ω is defined.)

w_a^ω Relief workers required to handle commodities at AA a (workers / ft^3×1000)

p^ω Probability of scenario ω occurring

Derived Sets:

L^S, L^M, L^D, A^R Subset of RLs, supply locations, shelter locations, and AAs with ramp space, respectively. E.g., $L^S = \{l \in L \mid s_l^0 > 0 \text{ or } s_l^{\max} > 0\}$

T^G, T^S Subsets of general mission MoT (i.e., $\bar{s}_t = 0,\ \bar{m}_t \geq 0, \bar{w}_t \geq 0, \bar{d} \geq 0$) and special mission MoT (i.e., $\bar{s}_t > 0,\ \bar{m}_t = \bar{w}_t = \bar{d}_t = 0$), respectively.

K Subset of four-tuples (t, l, a, l') where MoT t can travel from l to a and then to l': $\{(t,l,a,l') \in T \times L \times A \times L \mid h_{tla}^{\omega} + h_{tl'a}^{\omega} \leq \tau_t,\ t \in T_l \cap T_{l'}\}$, where τ_t is the operating range of t.

K^G, K^S Subsets of four-tuples (t, l, a, l') where general mission MoT t and special mission MoT t, respectively, can travel from l to a, and then to l':

$K^G = \{(t,l,a,l') \in K \mid t \in T^G; l, l' \in L^M \cup L^D\}$; $K^S = \{(t,l,a,l') \in K \mid t \in T^S, l' \in L^S\}$

First-Stage Decision Variables (units):

Δs_l Expansion for health capacity for EP at drop off RL l (persons)

Δm_l Expansion for co<u>m</u>modities at RL l (ft^3×1000)

Δr_a Expansion for <u>r</u>amp space at AA a (ft^3×1000)

Δd_l Expansion for DP at relief location l (persons)

Second-Stage Decision Variables (units), all under scenario ω:

Δu_t^{ω} Additional units of MoT t needed (vehicles)

$S_{tlal'}^{\omega}$ EP rescued by MoT t traveling from l to a and then l' (persons)

S_{ta}^{ω} Total EP rescued by MoT t at AA a (persons)

US_a^{ω} <u>U</u>nmet EP at AA a (including rescued but not surviving) (persons)

$M_{tlal'}^{\omega}$ Co<u>m</u>modities delivered by MoT t traveling from l to a and then l' (ft^3×1000)

M_{ta}^{ω} Total co<u>m</u>modities delivered by MoT t to AA a (ft^3×1000)

UM_a^{ω} <u>U</u>nmet co<u>m</u>modities at AA a (ft^3×1000)

$D_{tlal'}^{\omega}$ DP transported by MoT t traveling from l to a and then l' (persons)

D_{ta}^{ω} Total DP transported by MoT t from AA a (persons)

UD_{a}^{ω} Unmet transfer population at affected area a (persons)

$N_{tlal'}^{\omega}$ Number of trips from l to a and then to l' by MoT t (trips)

W_{ta}^{ω} Number of relief workers carried by MoT t to AA a (workers)

z_1, z_2 Objective value for the first goal (persons) and second goal (persons), respectively

Formulation:

Objective 1 (minimize): Expected Casualties from EP and AP:

$$z_1 = \sum_{\omega} p^{\omega} \sum_{a} \left(US_a^{\omega} + qUM_a^{\omega} \right) \tag{1.1}$$

Objective 2 (minimize): Expected Unmet DP:

$$z_2 = \sum_{\omega} p^{\omega} \sum_{a} UD_a^{\omega} \tag{1.2}$$

Budget:

$$\sum_{l \in L^S} c_l^S \, \Delta s_l + \sum_{l \in L^M} c_l^M \, \Delta m_l + \sum_{l \in L^D} c_l^D \, \Delta d_l + \sum_{a \in A^R} c_a^R \, \Delta r_a + \sum_{t} c_t^U \, \Delta u_t^{\omega} \le b, \forall \omega \tag{2}$$

MoT Available and Trips:

$$\Delta u_t^{\omega} \le u_t^{\max}, \forall t, \omega \tag{3.1}$$

$$\sum_{(l,a,l') | (t,l,a,l') \in K} (h_{tla}^{\omega} + h_{tl'a}^{\omega}) N_{tlal'}^{\omega} \le h_t (u_t^o + \Delta u_t^{\omega}), \forall t, \omega \tag{3.2}$$

$$\sum_{(l',a) | (t,l',a,l) \in K} N_{tl'al}^{\omega} = \sum_{(a,l') | (t,l,a,l') \in K} N_{tlal'}^{\omega}, \forall l, t \in T_l, \omega \tag{3.3}$$

EP and Its Transportation:

$$\Delta s_l \le s_l^{\max}, \forall l \in L^s \tag{4.1}$$

$$\sum_{(t,a) | (t,l,a,l') \in K^S} S_{tlal'}^{\omega} \le s_l^o + \Delta s_l, \forall l, l' \in L^s, \forall \omega \tag{4.2}$$

$$S_{tlal'}^{\omega} \le \overline{s}_t N_{tlal'}^{\omega}, \forall (t,l,a,l') \in K^S, \forall \omega \tag{4.3}$$

$$S_{ta}^{\omega} = \sum_{(l,l') | (t,l,a,l') \in K^S} S_{tlal'}^{\omega}, \forall a \in A, t \in T^S, \forall \omega \tag{4.4}$$

$$\sum_{t \in T^S} \lambda_a^{\omega} S_{ta}^{\omega} + US_a^{\omega} = s_a^{\omega}, \forall a, \omega \tag{4.5}$$

$$\sum_{t \in T^S} S_{ta}^{\omega} \le s_a^{\omega}, \forall a, \omega \tag{4.6}$$

Delivery of Commodities for AP:

$$\Delta m_l \le m_l^{\max}, \forall l \in L^M \tag{5.1}$$

$$\sum_{(t,a,l') | (t,l,a,l') \in K^G} M_{tlal'}^{\omega} \le m_l^o + \Delta m_l, \forall l \in L^M, \forall \omega \tag{5.2}$$

$$M_{tlal'}^{\omega} \le \overline{m}_t N_{tlal'}^{\omega}, \forall (t,l,a,l') \in K^G, \forall \omega \tag{5.3}$$

$$M_{ta}^{\omega} = \sum_{(l,l')|(t,l,a,l')\in K^G} M_{tlal'}^{\omega}\ , \forall t \in T^G, \forall a, \omega \tag{5.4}$$

$$\sum_{t\in T^G} M_{ta}^{\omega} + UM_{a}^{\omega} = m_{a}^{\omega}\ , \forall a, \omega \tag{5.5}$$

Sheltering DP:

$$\Delta d_l \le d_l^{\max}, \forall l \in L^D \tag{6.1}$$

$$\sum_{(t,l,a)|(t,l,a,l')\in K^G} D_{tlal'}^{\omega} \le d_{l'}^{o} + \Delta d_{l'}, \forall l' \in L^D, \forall \omega \tag{6.2}$$

$$D_{tlal'}^{\omega} \le \bar{d}_t\ N_{tlal'}^{\omega}, \forall (t,l,a,l') \in K^G, \forall \omega \tag{6.3}$$

$$D_{ta}^{\omega} = \sum_{(l,l')|(t,l,a,l')\in K^G} D_{tlal'}^{\omega}\ , \forall t \in T^G, \forall a, \omega \tag{6.4}$$

$$\sum_{t\in T^G} D_{ta}^{\omega} + UD_{a}^{\omega} = d_{a}^{\omega}, \forall a, \omega \tag{6.5}$$

Ramp Space:

$$\Delta r_a \le r_a^{\max}, \forall a \in A^R \tag{7.1}$$

$$\sum_{t\in T^R} M_{ta}^{\omega} \le r_a^{o} + \Delta r_a, \forall a \in A^R, \forall \omega \tag{7.2}$$

Relief Workers versus Commodities:

$$\sum_{t\in T^G} W_{ta}^{\omega} \ge w_a^{\omega} \sum_{t\in T^G} M_{ta}^{\omega}, \forall a, \omega \tag{8.1}$$

$$\bar{w}_t\, M_{ta}^{\omega} + \bar{m}_t W_{ta}^{\omega} \le \bar{w}_t\, \bar{m}_t \sum_{(l,l')|(t,l,a,l')\in K^G} N_{tlal'}^{\omega}, \forall t \in T^G, \forall a, \omega \tag{8.2}$$

$$\sum_{t\in T^G} W_{t,a}^{\omega} \le \overline{w_a}, \forall a, \omega \tag{8.3}$$

Domain for Decision Variables:

$$\Delta m_l,\ \Delta s_l,\ \Delta r_a,\ \Delta d_l,\ M_{tlal'}^{\omega},\ M_{ta}^{\omega},\ UM_{a}^{\omega},\ S_{tlal'}^{\omega},\ S_{ta}^{\omega},$$

$$US_{a}^{\omega},\ D_{tlal'}^{\omega},\ D_{ta}^{\omega},\ DM_{a}^{\omega} \ge 0, \qquad \forall t, l, l', a, \omega \tag{9.1}$$

$$\Delta u_t^{\omega},\ N_{tlal'}^{\omega},\ W_{ta}^{\omega}\ \ge 0 \text{ and integer}, \ \forall t, l, l', a, \omega \tag{9.2}$$

POM is a multi-objective model comprising two optimization problems (POs) hierarchically arranged. In the first one, PO-1, we minimize expected EP casualties including those who are non-rescued and those rescued but not surviving, and the AP casualties due to unmet commodities, as given by equation (1.1). The second problem, PO-2, minimizes unmet demand for transfer population (1.2):

$$\text{PO-1:}\quad z_1^* = \min\ z_1 \quad \text{s.t.} \begin{cases} (1.1) \\ (2)\text{-}(9.2) \end{cases}$$

$$\text{PO-2:}\quad z_2^* = \min\ z_2 \quad \text{s.t.} \begin{cases} (1.2) \\ (2)\text{-}(9.2) \\ z_1 \le (1+\alpha) z_1^* \quad (10) \end{cases}$$

Notice that PO-1 might be seen as a bi-objective problem itself, since it addresses two different groups of people. Our assumption is that both groups are equally important in the sense that failing to meet either demand results in casualties. Specifically, (1.1) accounts for casualties from the critical population, along with a fraction of those who do not receive commodities (q casualties per $\text{ft}^3 \times 1000$). PO-2 minimizes unmet demand for transfer population, but with the additional constraint (10) as an aspiration level based on PO-1's optimal solution. (In our test cases, we set the aspiration level to $\alpha = 1\%$.)

All of the remaining constraints are shared by both problems. (2) is the budget constraint. Most of the budget allocation is expected to occur during the first stage (expansion of medical facilities, warehouses, shelters, and ramp space). The remaining budget can be allocated to the engagement of additional MoT from the available fleet, usually commercial transportation, arranged beforehand to become available during a disaster, with contractual cost based on the level of utilization (thus, scenario-dependent). It is precisely these constraints that link decision variables involving critical population and commodities. Here, we note that a possible enhancement would be to capture the influx of any additional funding after the disaster has occurred. While part of this funding may be provided by private donors at the onset of a disaster for different purposes (such as financial help to individuals, reconstruction, etc.), we note that it is not complicated to accommodate an anticipated extra budget, b^{ω}, particular to each scenario, by simply adding b^{ω} to the right-hand side of equation (2). (This extension has not been explored in our experiments, i.e., we assume $b^{\omega} = 0$ for each ω.)

Constraints (3.1) bound the maximum capacity expansion for MoT, whereas (3.2) constraints ensure that travel time per MoT does not exceed their available operating hours. Constraints (3.3) are flow-balance constraints in and out of each RL. This is a global balance equation by MoT type, understanding that the actual schedule details of

each individual vehicle, aircraft, or vessel cannot be accurately anticipated and would become an unnecessary complication for long-term planning purposes.

Constraints (4.1) limit the allowable increase in healthcare providers located in the respective RLs. Constraints (4.2) limit the amount of EP that can be treated by available health providers. Constraints (4.3) ensure that these people are carried by an MoT configured for that special mission, traveling on a given route, but not exceeding the capacity. Constraints (4.4)–(4.6) account for the “met” and “unmet” demand of EP in each affected area. Specifically, the survival rate in (4.5) reflects that part of the EP rescued will perish.

Constraints (5.1) limit warehouse expansion. (5.2) limit delivery from eligible warehouses. (5.3) ensure that the commodities are carried by existing MoT configured for the general mission on each route. (5.4) and (5.5) account for the met and unmet demand of commodities for the AP at each AA. Likewise, (6.1)–(6.5) are constraints for sheltering DP.

Constraints (7.1) and (7.2) restrict ramp space expansion, which in turn limits commodities delivered by aircraft. Constraints (8.1) ensure that relief workers arrive at the AAs at a given rate based on the amount of commodities supplied to each affected area. Constraints (8.2) depict total capacity of an MoT on a general mission as a linear function of relief workers and commodities. Constraints (8.3) bound the maximum total capacity of the relief workers.

Finally, (9.1) and (9.2) define the appropriate domains for the decision variables.

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